6-13-2008

Two Essays on Managerial Behaviors in the Mutual Fund Industry Essay 1: A Life-Cycle Analysis of Performance and Growth in U.S. Mutual Funds Essay 2: Can Mutual Fund Window-Dressing Promote Fund Flows?

Leng Ling

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TWO ESSAYS ON MANAGERIAL BEHAVIORS
IN THE MUTUAL FUND INDUSTRY

BY

LENG LING

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree
of
Doctor of Philosophy
in the Robinson College of Business
of
Georgia State University

GEORGIA STATE UNIVERSITY
ROBINSON COLLEGE OF BUSINESS
2008

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor in Philosophy in Business Administration in the Robinson College of Business of Georgia State University.

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ABSTRACT

TWO ESSAYS ON MANAGERIAL BEHAVIORS
IN THE MUTUAL FUND INDUSTRY

By

LENG LING

June 4, 2008

Committee Chair: Dr. Gerald D. Gay and Jason T. Greene

Major Department: Finance

ESSAY 1: DOES MUTUAL FUND WINDOW-DRESSING PROMOTE
FUND FLOWS?

I investigate the effectiveness of window-dressing as a potential strategy to be used by mutual fund managers to promote fund flows. Using a rank gap measure as a proxy for the likelihood that window-dressing has occurred, I find that fund investors as whole punish those managers who are suspected to have engaged in window-dressing. That is, I find a negative relation between the window-dressing measure and net fund flows in subsequent quarters after controlling for fund performance, size, expense ratio, and other pertinent characteristics. I also find that window-dressing leads to higher trading activities and lower fund performance.

ESSAY 2: A LIFE CYCLE ANALYSIS OF PERFORMANCE AND GROWTH
IN U.S. MUTUAL FUNDS

I propose a five-stage growth model to describe the life cycle evolution of mutual funds and show that mutual funds exhibit distinctive performance, size, expense ratios, asset turnover, and other pertinent characteristics through stages of incubation, high-

growth, low-growth, maturity, and decline. I also investigate the viability of managerial strategies to affect a fund's life cycle evolution and find that changing a declining fund's investment objective is effective in rejuvenating asset growth and thus repositioning the fund to younger life cycle stages. However, the strategy of adding portfolio managers appears to have no such rejuvenation effect.

Does Mutual Fund Window-Dressing Promote Fund Flows?

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This version: June 3, 2008

Abstract

We investigate the effectiveness of window-dressing as a potential strategy to be used by mutual fund managers to promote fund flows. Using a rank gap measure as a proxy for the likelihood that window-dressing has occurred, we find that fund investors as whole punish those managers who are suspected to have engaged in window-dressing. That is, we find a negative relation between the window-dressing measure and net fund flows in subsequent quarters after controlling for fund performance, size, expense ratio, and other pertinent characteristics. We also find that window-dressing leads to higher trading activities and lower fund performance.

JEL Classification: G11; G20

Keywords: Mutual funds; Window dressing; Managerial behavior; Fund flows

* I thank my dissertation committee members, Gerald D. Gay (co-chair), Jason T. Greene (co-chair), Conrad S. Ciccotello, and Harley E. Ryan for their valuable advice. I am grateful to Mark Chen, Marcin Kacperczyk, Jayant Kale, Omesh Kini, Reza S. Mahani, and Laura Starks for their helpful comments and constructive suggestions. Any errors that remain are mine. Contact information: Department of Finance, J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303-3083. Tel: 1-404-413-7314; fax: 1-404-413-7312. E-mail address: lling1@gsu.edu.

1. Introduction

Mutual funds are required to report their portfolio holdings following the end of each quarter.[1] A number of articles in both financial press and academic literature suggest that prior to the reporting date some equity fund managers may engage in window-dressing, whereby they purchase or increase their holdings in stocks that have good performance recently (winners) and unload poorly performing stocks (losers) to look better to current and potential investors.[2] The underlying premise is that investors base their investment decisions on observed portfolio holdings, in addition to other information such as fund performance. Managers who window-dress expect fund investors to respond positively to a portfolio that shows more winners by adding investment and to withdraw money from a fund that holds more losers.

The extant mutual fund literature has found evidence consistent with window-dressing behavior of fund managers (see, Lakonishok, Shleifer, Thaler, and Vishny, 1991; Sias and Starks, 1997; He, Ng, and Wang, 2004; Ng and Wang, 2004; Meier and Schaumburg, 2004). These studies, however, do not investigate the effect of window-dressing on fund flows. We extend this literature by investigating the effectiveness of window-dressing as a strategy to promote fund

[1] Under the Securities Exchange Act of 1934 and the Investment Company Act of 1940, mutual fund managers were required to transmit a report to their shareholders semiannually. In 1975, Congress enacted section 13 (f) of the Securities Exchange Act to increase the public availability of information on securities holdings by institutional investors. Under this section, an institutional investment manager that exercises investment discretion over portfolios with an aggregate value of $100 million or more must file quarterly reports of portfolio holdings on Form 13F within 60 days after the end of each quarter. Although funds were required to report semiannually after an amendment in 1985, a majority of managers voluntarily disclose their portfolio holdings on a quarterly basis. Effective May 10, 2004, the U.S. Securities and Exchange Commission requires investment companies file their complete portfolio schedule as of the end of the first and the third fiscal quarters on Form N-Q, in addition to the annual and semiannual reports filed on Form N-CSR and N-CSRS, respectively. Furthermore, schedules must be filed within 60 days after the end of each quarter.
Source: (1) The Investment Company Act of 1940, Section 30. (2) The Securities Exchange Act of 1934, Section 13 (f). (3) Cici, Gibson, and Moussawi (2006). (4) http://www.sec.gov/rules/final/33-8393.htm#IB. (5) http://www.sec.gov/divisions/investment/guidance/13fpt2.htm.

[2] There could be other types of window dressing. (1) Managers may decrease their holdings in high-risky securities prior to the reporting date in order to make their portfolios appear less risky (Musto, 1997, 1999; Morey and O'Neal, 2006). (2) At the last trading date of the quarter, managers may purchase stocks already held to drive up stock prices and thereafter quarter-end fund values, a practice known as "portfolio pumping", "leaning for the tape", or "marking up" (Carhart, Kaniel, Musto, and Reed, 2002). (3) Managers may invest in securities that deviate from their stated fund objectives and eliminate those assets prior to the reporting date (Meier and Schaumburg, 2004).

flows, using a sample of 27,286 quarterly reports filed by actively managed U.S. equity funds for the period of March 1980 through December 2005.

This study also contributes to the literature by developing a new approach to detect unobserved window-dressing behavior of fund managers. Since window-dressing occurrence cannot be ascertained with certainty, we construct a rank gap measure as a proxy for the likelihood that window-dressing has occurred. The rationale for this approach is that, on average, a poorly performing fund has a high percentage of its assets invested in losers but low percentage in winners. In contrast, a well performing fund has the opposite. Thus, observing a poorly performing fund with a high percentage of assets in winners and a low percentage of assets in losers suggests a greater window-dressing likelihood. Based on this reasoning, for each quarter and each fund sector we rank funds in descending order by quarterly return and find the percentile rank of return, with funds in the first percentile being the best performing funds. Similarly, we find their percentile rank of winner proportion in descending order, where winner proportion is the percentage of a fund's assets invested in the winning stocks for the quarter. Also, we find their percentile rank of loser proportion in ascending order, where loser proportion is the percentage of a fund's assets invested in the losing stocks for the quarter.

In the absence of window-dressing, a poorly performing fund should have a low percentile rank of fund performance, a low percentile rank of winner proportion, and a low percentile rank of loser proportion. If a fund has a low percentile rank of performance but relatively high percentile ranks of winner and loser proportions, the resulting rank inconsistency suggests that the fund manager has engaged in window-dressing. The larger the rank inconsistency, the higher likelihood that window-dressing has occurred. We define the rank gap measure as the difference between the rank of fund performance and the average of the ranks of winner and loser proportions. The results of several tests strongly suggest that this measure is a reasonable proxy for the unobserved window-dressing behavior. For instance, we find that rank gap is positively related to trade volume in both contemporary and subsequent quarters, a relation that is consistent with the conventional understanding that window-dressing involves unnecessary trading activities of buying winners and selling losers.

The empirical results show that, on average, the window-dressing strategy does not promote fund flows. We find that net fund flows in the subsequent quarter are negatively related to the rank gap measure after controlling for fund performance and other pertinent characteristics including size, age, loads, expense ratio, asset turnover, and investment objective. It appears that fund investors indeed examine disclosed portfolio holdings. Furthermore, they infer managers' window-dressing behavior and punish suspected managers by reducing their investment in the funds. Further analysis shows that this negative response is from fund flows beginning in the third month of the next quarter. There is no statistically significant relation between window-dressing and fund flows in the first two months of the subsequent quarter. The U.S. Securities and Exchange Commission (SEC) requires mutual fund managers file their quarterly reports of portfolio holdings within 60 days after the end of a quarter. This rule actually allows managers to file their reports with delay. Using both SEC's Edgar database and Thomson Financial mutual fund holding database, we find that a large number of mutual funds delayed their reports for around 60 days. That means that investors typically do not observe portfolio holdings until two months after the end of the quarter. We also find that the effect of window-dressing on fund flows can last for two quarters.

Consistent with He, Ng, and Wang (2004) and Meier and Schaumburg (2004), we find that a manager is more likely to engage in window-dressing if his fund obtains lower past performance than his peers. Since window-dressing could be detected and punished with reduced fund flows, why do some managers especially those of poorly performing funds nevertheless do it and take the risk it involves? We propose that these managers adopt the window-dressing strategy to affect investors' perception of managers' stock selection skill, and they are able to hide their window-dressing strategy under some circumstances.

Because the SEC allows managers to file their reports with 60-day delay, a large number of mutual funds postpone their portfolio disclosure. Poorly performing managers could benefit from window-dressing with delayed reports. If a poorly performing manager window-dresses and fund performance improves for whatever reason in the subsequent quarter, it is not easy for investors to tell if this manager has engaged in window-dressing or he has stock selection skill as long as the disclosed winners do not depreciate much. Fund investors are likely to believe that this manager has stock selection skill because it is natural for investors to attribute improved fund performance to the disclosed high proportion of assets invested in winning stocks. On the other hand, if this unskilled manager experiences poor performance again in the following quarter, his window-dressing behavior will be detected. However, he has little to lose because he already faced a threat of being replaced at the end of the year because of the poor performance observed in the preceding quarter. In contrast, managers of well performing funds have lower incentives to window-dress because these managers benefit from good fund performance that attracts more investment and they do not want to be punished with reduced fund flows.

Kacperczyk, Sialm, and Zheng (2006) create a return gap measure, the difference between a fund's reported return and the return of a hypothetical portfolio that invests in the fund's disclosed end-of-period holdings. They propose that this measure captures the effect of multiple managerial actions including the pursuit of window-dressing behavior. For robustness, we repeat all analyses using return gap as a proxy for window-dressing. We find that fund flows in the first month of the quarter are sensitive to return gap of the prior quarter-ending month while fund flows in the second and third subsequent months are not. This finding is inconsistent with the fact that managers typically disclose their portfolio holdings with an approximate one to two months lag. We also perform tests that show that our rank gap measure contains more information to explain fund flows than return gap does.

The rest of the paper proceeds as follows. Section 2 reviews the literature. Section 3 describes the data and main variables used. Section 4 develops a rank gap measure to detect the unobserved window-dressing behavior of mutual fund managers. Section 5 investigates the effect of window-dressing on fund flows in subsequent periods. Section 6 reports the results of tests for robustness. Section 7 concludes this study.

2. Literature review

Lakonishok, Shleifer, Thaler, and Vishny (1991) examine the quarterly holdings of 769 equity pension funds from 1985 to 1989. They estimate purchase and sales based on portfolio changes over quarter-end and compare trading in the first three quarters with that in the fourth quarter. Their results show that funds sell more losers in the fourth quarter. Since their method compares the purchase and sales over quarter-end, it would not be able to test whether a fund manager has engaged in window-dressing during a particular quarter.

Sias and Starks (1997) examine the trading activity of individual and institutional investors at year-end and find that institutions sell fewer winners in the fourth calendar quarter than the first quarter of the subsequent year, which is consistent with the window-dressing hypothesis.

Following Lakonishok et al. (1991), He, Ng, and Wang (2004) examine the quarterly holdings of different types of institutions and show that banks, life insurance companies, mutual funds, and investment companies who invest on behalf of their clients sell more poorly performing stocks during the last quarter than the first three quarters of the year. Moreover, this trading behavior is more pronounced for institutions whose portfolios have underperformed the market. Ng and Wang (2004) investigate the relation between institutional trading and turn-of-the-year effect in stock returns. Their results indicate that institutions sell more extreme losing small stocks in the last quarter of the year but buy more small winners and small losers in the subsequent quarter. They conclude that this trading pattern of institutions reflects investment strategies that are consistent with window-dressing.

Meier and Schaumburg (2004) analyze the semiannual holdings and daily net asset values of 4,025 U.S. domestic equity mutual funds from 1997 to 2002. They compare the realized fund return with a hypothetical buy-and-hold return that the fund would have earned had it held the reported portfolio during the weeks leading up to the reporting date. The rationale for their method is that the hypothetical holding-based return will outperform the realized return if the trading due to window-dressing occurs over the last days of the quarter. Their empirical results show that the hypothetical returns are higher than the realized returns for some funds and that mutual funds with poor recent performance are more likely to window-dress.

Although previous studies provide evidence that is consistent with window-dressing behavior of fund managers, they do not examine the effect of window-dressing on fund flows. This paper fills in this blank by investigating the relation between fund flows and disclosed portfolio holdings, which could be subject to the unobserved window-dressing strategy.

3. Data

3.1. Data source

We create the main data set by merging the survivorship-bias-free mutual fund database from the Center for Research in Security Prices (CRSP) with the Thomson Financial mutual fund holding database and the CRSP stock database. The CRSP mutual fund database includes information on mutual fund monthly return, total net assets, inception date, fee structure, fund investment objective, asset turnover ratio, and other fund attributes. The Thomson Financial mutual fund database provides quarterly or semiannual holdings of most U.S. equity mutual funds. We merge these two databases using the MFLINKS database from Wharton Research Data Services (WRDS).

We exclude the balanced, bond, index, international, and sector funds to focus on actively managed equity funds that invest mainly in the U.S. stock market. We also exclude funds that are closed to new investors. We use the Wiesenberger (WI) fund type code, the ICDI fund objective code, and Standard & Poor’s detailed objective code to categorize funds as Growth, Growth and

Income, and Income funds.[3] One fund may have multiple share classes. Weighting each share class by its total net assets, we obtain the value-weighted averages of monthly and thereafter quarterly net return, expense ratio, turnover ratio, and total loads at the fund level. The total net assets of the fund equals the summation of total net assets of each share class.

We link individual stocks in fund portfolio to the CRSP stock database to find the stock performance over the preceding three months up to the last trading date of the quarter. We delete the holdings on funds, ADRs, bonds, foreign stocks, and preferred stocks, and exclude those reported portfolios that have less than 70% of the fund's assets invested in common stocks. Some holding stocks have missing prices or lack entries for the number of holding shares, and as a result we cannot determine their weights in portfolio. We discard a quarterly report if the number of missing-weight stocks over the number of all common stocks in portfolio yields a ratio larger than 1%. The final sample is composed of 27,286 quarterly reports from 2,336 equity funds that cover the period from March 1980 through December 2005.

Following Lakonishok et al. (1991) and He, Ng, and Wang (2004), at the end of each quarter we sort in descending order all domestic stocks in the CRSP into quintiles based on their returns over the past three months. The first quintile consists of stocks that achieve the highest returns. For each portfolio report, we identify stocks that belong to different return quintiles and then calculate the proportion of the fund's assets invested in the first and fifth quintile, respectively. We refer to these two proportions as the winner proportion and loser proportion.

We calculate monthly net fund flows as

$$TNA_t - TNA_{t-1} \cdot (1 + r_t) \, ,$$

[3] The Wiesenberger Fund Type Code (WI) is available through 1993. The ICDI Fund Objective Code (ICDI) is available from 1993 through July 2003. Standard &Poor's detailed objective code (S&P) begins in 1993, and formerly was the Strategic Insight Objective code. We categorize as "Growth" those funds with the WI code of SCG, AGG, G, LTG, MCG, G-S, S-G, and GRO, funds with the ICDI code of AG, AGG, and LG, and funds with the S&P code of SCG, AGG, and GRO. We categorize as "Growth and Income" those funds with the WI code of GCI, G-I, G-I-S, G-S-I, I-S-G, S-G-I, S-I-G, and GR, funds with the ICDI code of GI and TR, and funds with the S&P code of GRI, ING, and GMC. We categorize as "Income" those funds with the WI code of I, I-S, IEQ, and ING, funds with the ICDI code of IN, and funds with the S&P code of ING as "Income".

where TNA is the total net assets of the fund at the end of the month and r_t is the net return at month t. Quarterly fund flows are the summation of fund flows in the three consecutive months of the quarter.

3.2. Descriptive statistics

Table 1 presents descriptive statistics of the main variables used in analysis. The median (mean) of quarterly net fund flows is -0.23 (5.28) millions. The winner proportion has a median (mean) of 15.6% (17.4%) while the loser proportion has a median (mean) of 10.3% (11.1%). The data indicates that more assets are invested in winners than losers in the reported portfolios.

Correlation coefficients between variables are shown in Table 2. The winner proportion and loser proportion are negatively correlated, -0.20. This finding is conceivable because more investment in winners will lead to less investment in losers, given a fixed amount of fund assets. The correlation coefficient between the winner proportion and quarterly fund return is 0.19, which is consistent with the notion that a fund should have achieved good performance if it has a large proportion of the assets invested in winning stocks. The correlation between the loser proportion and quarterly fund return is -0.02.

4. The window-dressing measure

Without a time series data of a fund's daily holdings, fund investors do not know for sure that the manager has engaged in window-dressing. However, using all available public information, investors can infer the likelihood that window-dressing has occurred. Several financial service providers such as Yahoo!Finance and Morningstar provide easily accessible information such as monthly fund returns and top5 or top10 holdings of a fund. The SEC's Edgar database even provides for free the complete portfolio holdings reported by fund managers. Based on this public information, we construct a measure that indicates the likelihood that window-dressing has occurred.

4.1. Variable construction

For each quarter and each fund sector (Growth, Growth and Income, and Income), we sort funds in descending order by quarterly return and find their percentile rank of return, with funds in the first percentile being the best performing funds and funds in the 100th percentile being the worst. Then, we find their percentile rank of winner proportion, with funds in the first percentile having the highest winner proportion and funds in the 100th percentile having the lowest. Similarly, we sort funds in ascending order by loser proportion, with funds in the first percentile having the lowest loser proportion and funds in the 100th percentile having the highest. After these three independent sortings, we obtain the percentile rank of fund performance, the percentile rank of winner proportion, and the percentile rank of loser proportion for each fund.

In the absence of window-dressing, a well performing fund should have a high percentile rank of fund performance, a high percentile rank of winner proportion, and a high percentile rank of loser proportion. On the contrary, a poorly performing fund should have a low percentile rank of fund performance, a low percentile rank of winner proportion, and a low percentile rank of loser proportion. These relationships are shown in the Appendix. If a fund has a low percentile rank of performance but relatively high percentile ranks of winner and loser proportions, this rank inconsistency suggests that the fund manager may has engaged in window-dressing. The larger the rank inconsistency, the higher the probability that window-dressing has occurred. We define the rank gap measure for window-dressing, WD, as

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2},$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. The theoretical bound of rank gap is [-99, 99], while we find that the median (mean) of this measure is –1 (-0.0029) and its range is [-96.5, 99].

4.2. Trading activity

In this section, we investigate the relation between the rank gap measure and managers' trading activity. Window-dressing involves unnecessary trading activities that buy winners and sell losers prior to the end of the quarter. Thus, a window-dresser would trade more than he does in the absence of window-dressing. If our measure catches the window-dressing behavior, we should observe a positive relation between this measure and the trade volume (in dollars) of the contemporary quarter.

The Thomson Financial database reports net changes in shares since prior reports. Using these share change data we calculate trade volume scaled by the total net assets for each net share change. We obtain the total trade volume for a given quarter by adding up all individual trade volume, as window-dressing involves both buying winners and selling losers.[4] Then we estimate an OLS regression model of quarterly trade volume on contemporary rank gap, controlling for fund performance and other fund characteristics.

$$TradeVolume_{i,t} = \alpha + \beta_1 WD_{i,t} + \psi \mathrm{X}_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where **X** is a vector of control variable that includes fund performance, size, loads, expense ratio, age, flows, and dummies for investment objective, fund, and year. The standard errors are robust to heteroskedasticity and are clustered at the fund level.

The results reported in Table 3 indicate a positive relation between the rank gap measure and trading activity of the current quarter. In model 1 where funds are evaluated on quarterly return, the coefficient of rank gap is 0.0005 with the 1% significance level. Higher past return is associated with higher trading activity. Larger fund size leads to lower trading activity, a causality

[4] We recognize that this "trade volume" overlooks the interim trading.

that could be traced to the less flexibility in changing portfolio holdings. When funds are evaluated on their returns over the past 12 months, we obtain very close results reported in regression model 2.

It is very likely that after the reporting date a window-dressing manager will rebalance his portfolio and shift back to the original portfolio before window-dressing. In that case, there will be additional trading in the subsequent quarter. To test the relation between the rank gap measure and trading activity in the following period, we estimate a regression model of quarterly trade volume on lagged rank gap, while controlling for other fund characteristics.

$$TradeVolume_{i,t} = \alpha + \beta_1 WD_{i,t-1} + \psi \mathrm{X}_{i,t-1} + \varepsilon_{i,t} \ , \tag{2}$$

where **X** is a vector of control variable that includes lagged fund performance, size, loads, expense ratio, age, flows, and dummies for investment objective, fund, and year. The regression results summarized in Table 4 show that higher rank gap leads to higher trade volume in the subsequent quarter. The coefficients of rank gap in model 1 and model 2 are 0.0208 and 0.0152, respectively, and both are statistically significant at the 1% level.

Overall, the findings on trade volume in both contemporary and subsequent quarters are consistent with the conventional understanding of window-dressing that this strategy involves higher trading activities than in the absence of window-dressing.

4.3. Momentum strategy

Fund managers who embark on a momentum strategy will buy winners and sell off losers when adjusting their portfolios. A fund that window-dresses and another fund that pursues a momentum strategy can exhibit similar allocation of assets. That is, more investment in winners than losers. If our rank gap measure is unable to discriminate between a window-dressing and momentum strategy, its viability to detect window-dressing may be called into question.

Consequently, we test the measure to ensure that it is a good proxy for the window-dressing behavior rather than the momentum strategy.

Jegadeesh and Titman (1993) compare 16 momentum strategies that select stocks based on their returns over the past one, two, three, and four quarters and hold portfolios for periods that vary from one to four quarters. They refer to a strategy that selects stocks based on their returns over the past J months and holds them for K months as a J-month/K-month strategy. Their results show that all those portfolio returns are statistically significant except for the three-month/three-month strategy. Four portfolios that select stocks based on their returns over the past three months obtain the lowest returns among the 16 strategies. Keeping the three-month holding period constant, the momentum profits increase as J increases. Among the 16 strategies, the most successful one is the 12-month/three-month strategy.

Since our window-dressing measure is constructed based on stock performance over the past three months and recalculated every three months, it may catch the three-month/three-month momentum strategy if mutual fund managers indeed adopt this particular strategy that selects stocks based on their returns over the past three months and holds them for one quarter. Nevertheless, fund managers should not have incentives to employ such a momentum strategy because, as showed in Jagadeesh and Titman (1993), this strategy does not produce momentum returns. Therefore, the rank gap measure constructed from empirical data can not happen to be a proxy for a “momentum strategy” that was unlikely to be used by mutual fund managers.

The extant literature finds strong evidence that the momentum strategy is associated with higher returns in the following periods (see, e.g., Jegadeesh and Titman, 1993; Carhart, 1997; Sias, 2007). Accordingly, if rank gap catches the momentum strategy, there should be a positive relation between this measure and fund performance in the next quarter. To test this conjecture, we estimate a regression model of quarter fund return on lagged rank gap while controlling for fund performance and other pertinent characteristics.

$$\mathrm{Re}\,turn_{i,t} = \alpha + \beta_1 WD_{i,t-1} + \psi \mathrm{X}_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

Table 5 summarizes the regression results. In model 1 where funds are evaluated by their quarterly performance, the coefficient of rank gap is -0.0006 and statistically significant at the 1% level. It indicates that a larger rank gap will lower fund performance in the next quarter, which is inconsistent with the nature of the momentum strategy. On the contrary, this evidence is consistent with the conventional notion that window-dressing destroys value and drags down fund performance mainly because of additional trading costs. Similar results are found in model 2 where funds are evaluated by their performance over the past 12 months up to the last date of the quarter.[5]

The unnecessary trading involved in window-dressing incurs additional transaction costs, which would also drag down performance of the quarter-ending month. We estimate a regression model of quarter-ending month return on rank gap and find a negative relation. This unreported evidence reaffirms the previous finding that window-dressing destroys fund value.

A manager that pursues a momentum strategy will always buy winners and sell off losers, regardless of past fund performance. As a result, a negative relation between past fund performance and a proxy for the momentum strategy is unlikely to occur. In contrast, prior studies such as He, Ng, and Wang (2004) and Meier and Schaumburg (2004) find that poorly performing funds are more likely to window-dress. To further investigate whether our measure is a reasonable proxy for window-dressing, we perform a multivariate analysis on the relation between rank gap and past fund performance.

Considering managers may have extraordinary incentive to window-dress if their performance is extremely poor compared to their peers, we estimate a quadratic relation between window-dressing and past fund performance. We rank funds into quintiles based on quarterly (annual) returns and group the three middle quintiles together. Funds belonging to the fifth

[5] In a robustness test, we observe a negative relation between rank gap and fund return in the successive month.

quintile are the best performing funds. Then we create two dummies, r_q234 and r_q5, for funds located in the middle quintiles and the fifth quintile, respectively. We estimate the following regression model,

$$WD_{i,t} = \alpha + \beta_1 r\_q234_{i,t} + \beta_2 r\_q5_{i,t} + \psi \mathrm{X}_{i,t} + \varepsilon_{i,t} \,. \tag{4}$$

Table 6 reports the results. In model 1, funds are ranked by quarterly returns. The estimate of the coefficient of performance dummy for middle quintiles is -24.6419 while that of the fifth quintile is -49.8833. Both estimates are statistically significant at the 1% level. Model 2 uses ranks of past annual performance and generates consistent results. The negative relation between past fund performance and the rank gap measure is consistent with He, Ng, and Wang (2004) and Meier and Schaumburg (2004) in that poorly performing funds are more likely to window-dress.

In summary, the findings in prior studies and the new evidence shown above indicate that the rank gap measure is inconsistent with the momentum strategy and that it is a reasonable proxy for the unobserved window-dressing strategy employed by mutual fund managers to promote fund flows.

5. Fund flows

5.1. Window-dressing and fund flows

In this section we investigate the effect of window-dressing on fund flows in subsequent quarters. We estimate the following regression model,

$$Flows_{i,t} = \alpha + \beta_1 WD_{i,t-1} + \beta_2 WD_{i,t-2} + \psi \mathrm{X}_{i,t-1} + \varepsilon_{i,t} \,, \tag{5}$$

where Flows is quarterly fund flows measured in millions of U.S. dollars; **X** is a vector of control variable that includes lagged fund performance, size, loads, expense ratio, turnover, age, flows in the prior quarter, and dummies for investment objective, fund, and year.

The regression results of model 1 and model 2 reported in Table 7 indicate a negative relation between the rank gap measure and fund flows in subsequent quarters. In model 1, funds are evaluated and ranked by quarterly returns. The coefficient of rank gap in the last quarter is -0.0505 at the 5% significance level while that for the second-last quarter is -0.1556 at the 1% significance level. The coefficient of the middle quintiles in performance rank is 3.7884 while that of the fifth quintile is 8.3257, and both are statistically significant at the 1% level. This convexity between performance and flows is consistent with the extant literature (see, e.g., Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). These results are robust when funds are valuated by annual returns, as shown in model 2. It is evident that fund investors infer managers' window-dressing behavior and reduce their investment if they suspect window-dressing has occurred.[6]

We examine the multicollinearity between independent variables and find that all variables (excluding sector dummy, fund dummy, and year dummy) have a variance inflation factor (VIF) below two, which is much lower than the critical value of 10. This finding suggests that the negative relation between window-dressing and fund flows is not driven by the negative relation between performance and flows.

The negative response of fund flows to window-dressing behavior of managers is conceivable. Window-dressing involves unnecessary trading activities that are costly. Funds incur both explicit and implicit trading costs such as brokerage commissions and price impact. These transaction costs will drag down the net returns to investors because the Net Asset Value (NAV) of a fund is calculated after the deduction of all costs. In addition, the portfolio composition subject to window-dressing can mislead investors when they make investment decisions. As a result, window-dressing incurs high agency costs without adding any value for fund investors. Because window-dressing is contrary to the best interests of fund investors, investors will respond

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[6] We also estimate a quadratic relation between rank gap and fund flows and find supportive evidence. Since the quadratic performance-flows relation exhibits a deeper slope in higher returns while the quadratic relation between rank gap and flows shows a deeper slope in lower returns, this difference implies that the negative relation between rank gap and flows is not because of performance.

negatively by reducing their investment in suspected funds that have exhibited high window-dressing likelihood.

5.3. Different flow sensitivity to lag1_WD and lag2_WD

One interesting finding that deserves more attention is that quarterly fund flows are less sensitive to window-dressing in the immediately past quarter than to that in the second to last quarter. Wald test indicates that the coefficients of lag1_WD and lag2_WD are different from each other at the 1% significance level. We argue that the reason for this difference in flow sensitivity lies in the fact that fund investors, in general, do not observe disclosed portfolio holdings until typically two months after the end of the quarter.

Under the Investment Company Act of 1940, the SEC requires mutual fund managers file their quarterly reports of portfolio holdings within 60 days after the end of a quarter. This rule actually allows managers to file their reports with delay. To obtain a better idea of how much fund managers delay their reports, we randomly choose 20 equity funds from Yahoo!Finance and use the SEC's Edgar database to find the time lag between the reporting date and the filing date. We find that 19 of these randomly chosen funds filed their reports at least 50 days after the end of the quarter and one fund filed its reports after a 40-day delay. We also examine the Thomson Financial mutual fund holding database and find similar evidence that a large number of mutual funds delay their reports.

Quarterly fund flows are the summation of flows in three successive months. Since investors do not observe disclosed portfolio holdings until two months after the reporting date, the rank gap measure can explain some variation of fund flows beginning in the third month of the subsequent quarter, but not that in the first two months. During all three months of the subsequent second quarter, more investors will have examined the disclosed portfolios and responded negatively to suspected window-dressing behavior. Accordingly, we should observe a higher sensitivity of fund flows to window-dressing in the second-last quarter. To test this hypothesis that only flows occurred in the third month are sensitive to lag1_WD while flows in all three months are sensitive to lag2_WD, we estimate such simultaneous equations,

$$\begin{aligned}
Flows_{i,t,1} &= \alpha_1 + \beta_1 WD_{i,t-1} + \beta_2 WD_{i,t-2} + \psi \mathrm{X}_{i,t-1,1} + \varepsilon_{i,t,1} \\
Flows_{i,t,2} &= \alpha_2 + \beta_1 WD_{i,t-1} + \beta_2 WD_{i,t-2} + \psi \mathrm{X}_{i,t-1,2} + \varepsilon_{i,t,2} \\
Flows_{i,t,3} &= \alpha_3 + \beta_1 WD_{i,t-1} + \beta_2 WD_{i,t-2} + \psi \mathrm{X}_{i,t-1,3} + \varepsilon_{i,t,3}
\end{aligned} \tag{6}$$

where $Flows_{i,t,1}$ is fund i's net flows in the first month of the quarter; $Flows_{i,t,2}$ is flows in the second month of the quarter; $Flows_{i,t,3}$ is flows in the third month of quarter t;. **X** is a vector of control variables that include lagged fund performance, size, loads, expense ratio, turnover, age, preceding monthly flows, and dummies for investment objective, fund, and year. We report the regression results in Table 8.

It appears that flows that occurred in the first two months of the quarter are not sensitive to lag1_WD while flows that occurred in the third month of the quarter exhibit strong sensitivity. The coefficient of lag1_WD of the third-month flow model, -0.0493, is very close to that in model 1 of Table 7, -0.0505. Furthermore, fund flows in all three successive months are sensitive to lag2_WD. This evidence is consistent with our hypothesis that investors do not observe disclosed portfolio holdings and therefore infer window-dressing until about two months later after the end of the quarter. This evidence suggests that our rank gap measure is a good proxy for window-dressing.

5.4. Incentives to window-dress

Compensations to mutual fund managers are linked to fund size. Therefore, managers have strong incentive to retain and attract assets under management. It is said that the reason for fund managers to window-dress is to please current investors and attract new money. However, we find that fund flows are negatively related to window-dressing. Does it mean mutual fund window-dressing is an irrational behavior? We propose two reasons for the adoption of window-dressing by some fund managers.

Firstly, window-dressing may successfully allure some investors, especially those who are not well investment-educated and who do not realize the existence of window-dressing. Less complicated investors are more likely to be attracted by mutual funds' top 5 or top 10 holdings, which could be manipulated with window-dressing.

Second, poorly performing managers could benefit from window-dressing with delayed reports. As mentioned earlier, a large number of fund managers do not file their reports until around 60 days later. If the manager of a poorly performing fund window-dresses and fund performance improves for whatever reason in the subsequent quarter, it is hard for investors to tell if this manager has engaged in window-dressing or he has stock selection skill as long as the disclosed winners do not depreciate much. Fund investors are likely to believe that this manager has stock selection skill because it is natural for investors to attribute improved fund performance to the disclosed high proportion of assets invested in winning stocks. On the other hand, if this unskilled manager experiences poor performance again in the following quarter, his window-dressing behavior will be detected. However, he has little to lose because he already faced a threat of being replaced at the end of the year because of the poor performance observed in the preceding quarter.

6. Robustness

We repeat all multivariate analysis by estimating panel regression models with fixed effect and random effect specifications. The results do not change much. We still find strong evidence that rank gap is a reasonable measure for window-dressing and that there is a negative relation between rank gap and fund flows.

There is a Tax-Loss Selling Hypothesis in the literature that investors will sell off losing stocks at the fourth quarter to realize investment loss, which investors can use to offset capital gains and therefore lower their personal tax liability. Managers are agents of fund investors and therefore may embark on tax-loss selling on behalf of fund investors. To exclude the possibility that our measure might catch this "tax-loss selling" behavior that occurs only at the fourth quarter, we repeat all multivariate analysis using observations of the first three calendar quarters. Still, we obtain very consistent results.

We construct a new variable, WD_dummy, that equals one if rank gap is positive and zero otherwise. We estimate the regression model (1) to (6) with this alternative window-dressing measure and obtain similar interpretation and conclusions. The results reported in Table 9 reaffirm that there is a negative relation between window-dressing and fund flows in subsequent quarters.

Kacperczyk, Sialm, and Zheng (2006) estimate the impact of managers' unobserved actions on fund returns using return gap, the difference between a fund's reported fund return and the return of a hypothetical portfolio that invests in the fund's disclosed end-of-period holdings. They argue that this return gap measure captures the effect of multiple managerial actions including interim trading, momentum strategies, and the pursuit of window-dressing behavior. If a manager window-dresses, the reported return would under-perform the hypothetical return. Accordingly, a negative return gap would suggests that window-dressing may have occurred. Thus, their measure could be a proxy for window-dressing. To have a better understanding of the relation between our measure and the return gap measure, we follow Kacperczyk et al. (2006) and compute the return gap measure for the quarter-ending months.

Consistent with the findings in Kacperczyk et al. (2006), we find that the mean of the hypothetical return of the quarter-ending month is 0.989%. If a fund has engaged in window-dressing near the end of the quarter, the hypothetical return would be higher than the reported return leading to a negative return gap. Thus, there should be a negative correlation between the return gap and rank gap measure if return gap contains some information of window-dressing and if rank gap is a reasonable proxy for window-dressing. We find that the correlation coefficient between rank gap and return gap is -0.15 with the 1% significance level. This observation suggests that rank gap and return gap share some information regarding the likelihood of unobserved window-dressing behavior.

Next, we test the relation between return gap and fund flows. Since a negative return gap suggests that window-dressing may have occurred, we should observe a positive relation between this measure and fund flows in the third month of the subsequent quarters. However, we should not observe a relation between return gap and flows in the first and second month because investors do not observe disclosed portfolio holdings until two months after the end of the quarter. We estimate the regression model (6) using return gap as a proxy for window-dressing. The regression results are summarized in Table 10. We observe that fund flows in the first month of a quarter are positively related to return gap of the last quarter-ending month while flows in the second and third month are not. This finding is inconsistent with the fact that investors do not observe the disclosed portfolio holdings until about two-months later because managers delay reports.

To further explore whether the rank gap measure provides information beyond that contained in the return gap measure, we conduct a J-test for testing between non-nested regression models.[7] First, we estimate a regression model of the third-month flows on the rank gap measure and calculate the set of fitted value for the dependent variable. Then, we estimate a regression model of the third-month flows on the return gap measure and calculate the set of fitted value for the dependent variable. Next, we estimate the rank gap model again, but also using the fitted value obtained from the return gap model as an added explanatory variable. We also estimate the return gap model again, but also using the fitted value obtained from the rank gap model as an added explanatory variable. The null hypothesis is that the rank gap model fit the data better than the model using the return gap measure. The null hypothesis is supported if the estimate of the coefficient of the fitted value from the rank gap model is significantly different

[7] Please see Davidson and MacKinnon (1981) and McAleer (1995) for a discussion of the J-test procedure.

from zero and the estimate of the coefficient of the fitted value from the return gap model is not significant. If both estimates of the coefficient of the fitted value from the return gap model and rank gap model are significantly different from zero, then each measure provides a degree of information not found in the other measure and the null hypothesis is rejected. If both estimates are insignificant, then the two measures provide similar information.

We present the J-test results in Table 11 in which we show the estimates of the coefficient of the added fitted value. The estimate of the coefficient of the fitted value from the return gap model is not statistically different from zero, while the estimate of the coefficient of the fitted value from the rank gap model is statistically significant at the 1% level. It appears that the rank gap measure provides information beyond that contained in the return gap measure.

7. Conclusions

Exploring a sample of 27,286 quarterly reports of 2,336 actively managed U.S. equity funds, this paper examines the window-dressing behavior of fund managers as a strategy to attract fund flows. We construct a rank gap measure to detect the unobserved window-dressing behavior. The rationale for this approach is that, on average, a poorly performing fund should have a high proportion of its assets invested in losers but low proportion in winners. Thus, observing a poorly performing fund with a high proportion of assets in winners and a low proportion in losers suggests a greater probability that window-dressing has occurred. Several tests provide supportive evidence that this rank gap measure is a reasonable proxy for the unobserved window-dressing behavior of fund managers.

Window-dressing involves unnecessary trading activities that buy winners and sell losers prior to the end of the quarter. Thus, a window-dresser would trade more than he does in the absence of window-dressing. We find a positive relation between window-dressing and trade volume of both contemporary and subsequent quarters. The unnecessary trading involved in window-dressing incurs additional transaction costs such as brokerage commission and price impact, which drags down fund performance. We find consistent evidence that window-dressing destroys fund value.

Trading involved in window-dressing incurs high costs. In addition, the portfolio composition subject to window-dressing can mislead investors when they make investment decisions. As a result, window-dressing incurs high agency costs without adding any value for fund investors. Because window-dressing is contrary to the best interests of fund investors, investors will respond negatively by reducing their investment in suspected funds that have exhibited high window-dressing likelihood. Consistent with this reasoning, the empirical analysis shows that net fund flows in subsequent quarters are negatively related to the rank gap measure after controlling for fund performance and other pertinent characteristics. This evidence suggests that fund investors infer window-dressing and reduce their investment in suspected funds. These findings indicate that on average the window-dressing strategy does not promote fund flows.

Our empirical findings also suggest that managers of poorly performing funds are more likely to engage in window-dressing than managers of well performing funds. Managers of well performing funds have low incentives to window-dress because they have earned good image and do not want to be punished with reduced net fund flows. In contrast, managers of poorly performing funds have high incentives to window-dress because they wish to influence investors' perception of their stock selection skill. Many fund managers delay their quarterly report for about two months and window-dressing managers benefit from this report-file lag. If a poor performing manager window-dresses and fund performance improves over the next quarter, fund investors may believe that this manager has stock selection skill because it is natural for investors to attribute improved fund performance to the disclosed high proportion of assets invested in winners. As a result, the manager could hide his type. Even if fund performance in the subsequent quarter is poor again and thus his window-dressing behavior is identified, the manager has little to lose because he already faced a threat of being replaced at the end of the year because of the poor performance observed in the preceding quarter.

Appendix

This appendix explains the construction of the rank gap measure for window-dressing. For each quarter we sort in descending order all domestic stocks in the CRSP into quintiles based on their quarterly returns. Stocks in the first quintile are winning stocks and those in the fifth quintile are losing stocks. For each quarter and each fund sector (Growth, Growth and Income, and Income), we sort funds in descending order by quarterly return, with funds in the first percentile being the best performing funds. Then, we sort funds in descending order based on winner proportion, which is the percentage of the assets invested in the winning stocks for the quarter. Similarly, we sort funds in ascending order by loser proportion, which is the percentage of the assets invested in the losing stocks for the quarter. After these three independent sortings, we obtain the percentile rank of fund performance, the percentile rank of winner proportion, and the percentile rank of loser proportion for each fund. We define the rank gap measure for window-dressing as

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. The theoretical bound of the rank gap measure is [-99, 99]. A larger rank gap indicates a higher likelihood that window-dressing has occurred.

Rank	Fund Performance	Winner Proportion	Loser Proportion
1	1 (best performance)	1 (highest proportion)	1 (lowest proportion)
2	2	2	2
3	3	3	3
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
98	98	98	98
99	99	99	99
100	100 (worst performance)	100 (lowest proportion)	100 (highest proportion)

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Table 1
Summary Statistics for Mutual funds

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. Flow is the quarterly fund flows measured in millions of U.S. dollars. Winner_prop is the proportion of the assets invested in winning stocks. Loser_prop is the proportion of the assets invested in losing stocks. In each quarter we sort in descending order all domestic stocks in the CRSP into quintiles based on their quarterly returns. Stocks in the first quintile are winning stocks and those in the fifth quintile are losing stocks. quarter_return is the total return of the fund over a quarter. TNA is the total net assets. Load is the total front-end, deterred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. Age is the number of years from the inception date up to the end of the quarter. All variables are winsorized at one and the 99th percentile.

Variable	Median	Mean	Std. Dev.	Min	Max
flow (million)	-0.23	5.28	75.6	-270	440
winner_prop (%)	15.6	17.4	11.5	0	52.7
loser_prop (%)	10.3	11.1	6.4	0	31.8
quarter_return (%)	4.0	4.8	11.6	-25.6	42.5
TNA (million)	163	685	1575	2	11037
load (%)	0.57	2.08	2.42	0	9.50
expense (%)	1.25	1.33	0.46	0.36	2.97
turnover (%)	65	88	80	2	462
Age (year)	8	12.8	13.7	0.1	82.6

Table 2
Correlation Matrix

This table reports the Pearson correlation coefficient between main variables. The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. Flow is the quarterly fund flows measured in millions of U.S. dollars. Winner_prop is the proportion of the assets invested in winning stocks. Loser_prop is the proportion of the assets invested in losing stocks. In each quarter we sort in descending order all domestic stocks in the CRSP into quintiles based on their quarterly returns. Stocks in the first quintile are winning stocks and those in the fifth quintile are losing stocks. quarter_return is the total return of the fund over a quarter. LogTNA is the logarithm of (1+ total net assets). Load is the total front-end, deferred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

	flow	winner_prop	loser_prop	quarter_r	logTNA	load	expense	turnover
winner_prop	0.06 ***							
loser_prop	-0.02 ***	-0.20 ***						
quarter_r	0.11 ***	0.19 ***	-0.02 ***					
logTNA	0.08 ***	-0.04 ***	-0.03 ***	0.06 ***				
load	-0.02 ***	-0.04 ***	-0.01	-0.04 ***	0.14 ***			
expense	-0.03 ***	0.12 ***	0.08 ***	-0.02 ***	-0.36 ***	0.30 ***		
turnover	-0.03 ***	0.27 ***	0.03 ***	0.04 ***	-0.12 ***	-0.01 **	0.22 ***	
logAge	-0.04 ***	-0.10 ***	-0.05 ***	-0.03 ***	0.49 ***	0.19 ***	-0.23 ***	-0.12 ***

Table 3
Regression of trade volume on contemporary rank gap

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variable is quarterly trade volume in dollars scaled by total net assets, which is obtained from net changes in holdings shares since the prior quarterly report. WD is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. quarter_return is the total return of the fund over the quarter. year-return is the total return of the fund over the past 12 months. logTNA is the logarithm of (1+ total net assets). Expense is the expense ratio. Load is the total front-end, deterred and rear-end charges. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1		Model 2	
WD	0.0005	***	0.0004	***
	0.00		0.00	
quarter_return	0.0010	***		
	0.00			
year_return			0.0002	***
			0.00	
logTNA	-0.0264	***	-0.0263	***
	0.00		0.00	
load	0.0036		0.0036	
	0.13		0.129	
expense	-0.0033		-0.0025	
	0.79		0.84	
logAge	-0.0590	***	-0.0574	***
	0.00		0.00	
flow	0.0001	**	0.0001	**
	0.02		0.03	
sector dummy	Yes		Yes	
fund dummy	Yes		Yes	
year dummy	Yes		Yes	
Adjusted R^2	0.38		0.38	
observation	24433		24433	

Table 4
Regression of trade volume on lagged rank gap

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variable is quarterly trade volume in dollars scaled by total net assets, which is obtained from net changes in holdings shares since the prior quarterly report. WD is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. quarter_return is the total return of the fund over the quarter. year-return is the total return of the fund over the past 12 months. logTNA is the logarithm of (1+ total net assets). Expense is the expense ratio. Load is the total front-end, deterred and rear-end charges. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. All control variables are lagged for one period. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1		Model 2	
lag1_WD	0.0208	***	0.0152	***
	0.00		0.01	
lag1_quarter_return	0.0198			
	0.18			
lag1_year_return			-0.0183	
			0.13	
lag1_logTNA	-0.9745	***	-0.8893	***
	0.00		0.00	
lag1_load	0.0729		0.0789	
	0.73		0.70	
lag1_expense	1.6789		1.7545	
	0.14		0.12	
lag1_logAge	1.7991	*	1.8395	*
	0.06		0.06	
lag1_flow	0.0053		0.0073	
	0.65		0.55	
sector dummy	Yes		Yes	
fund dummy	Yes		Yes	
year dummy	Yes		Yes	
Adjusted R^2	0.14		0.14	
observation	23244		23244	

Table 5
Regression of funds' quarterly return on lagged rank gap

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variable is the total return of the fund over the quarter. WD is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. quarter_return is the total return of the fund over the quarter. year-return is the total return of the fund over the past 12 months. logTNA is the logarithm of (1+ total net assets). Load is the total front-end, deterred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. All control variables are lagged for one period. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1		Model 2	
lag1_WD	-0.0006	***	-0.0003	***
	0.00		0.00	
lag1_quarter_return	-0.0022	***		
	0.00			
lag1_year_return			-0.0004	***
			0.00	
lag1_logTNA	-0.0114	***	-0.0120	***
	0.00		0.00	
lag1_load	0.0008		0.0008	
	0.35		0.30	
lag1_expense	-0.0019		-0.0035	
	0.66		0.40	
lag1_turnover	0.0001	***	0.0001	***
	0.00		0.00	
lag1_logAge	0.0141	***	0.0110	***
	0.00		0.00	
lag1_flow	0.0001	***	0.0001	***
	0.00		0.00	
sector dummy	Yes		Yes	
fund dummy	Yes		Yes	
year dummy	Yes		Yes	
Adjusted R^2	0.29		0.25	
observation	27069		27069	

Table 6
Regression of rank gap on fund return

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variable is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. We rank funds in ascending order into quintiles based on quarterly return and group the three middle quintiles together. quarter_q234 and quarter_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile, respectively. Similarly, year_r_q234 and year_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile when funds are ranked based on annual return. logTNA is the logarithm of (1+ total net assets). Load is the total front-end, deterred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1		Model 2	
quarter_r_q234	-24.6419	***		
	0.00			
quarter_r_q5	-49.8833	***		
	0.00			
year_r_q234			-14.2147	***
			0.00	
year_r_q5			-28.0951	***
			0.00	
logTNA	-0.4658	*	0.7545	***
	0.08		0.01	
load	0.0118		-0.1069	
	0.96		0.67	
expense	3.1248	***	4.5943	***
	0.00		0.00	
turnover	0.0268	***	0.0213	***
	0.00		0.00	
logAge	2.1788	***	2.2693	**
	0.01		0.02	
flow	-0.0381	***	-0.0507	***
	0.00		0.00	
sector dummy	Yes		Yes	
fund dummy	Yes		Yes	
year dummy	Yes		Yes	
Adjusted R^2	0.44		0.20	
observation	26868		26868	

Table 7
Regression of quarterly flows on rank gap

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variable is quarterly fund flows measured in millions of U.S. dollars. WD is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. We rank funds based on quarterly return in ascending order into quintiles and group the three middle quintiles together. quarter_q234 and quarter_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile, respectively. Similarly, year_r_q234 and year_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile when funds are ranked based on annual return. logTNA is the logarithm of (1+ total net assets). Load is the total front-end, deterred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. All control variables are lagged for one period. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1		Mode 2	
lag1_WD	-0.0505	**	-0.0464	**
	0.04		0.02	
lag2_WD	-0.1556	***	-0.1125	***
	0.00		0.00	
lag1_quarter_r_q234	3.7884	***		
	0.00			
lag1_quarter_r_q5	8.3257	***		
	0.00			
lag1_year_r_q234			5.9100	***
			0.00	
lag1_year_r_q5			19.1683	***
			0.00	
lag1_logTNA	1.2956		0.8488	
	0.44		0.62	
lag1_load	2.3526	**	2.1547	**
	0.02		0.03	
lag1_expense	-0.3624		-0.3756	
	0.91		0.90	
lag1_turnover	-0.0238	**	-0.0239	**
	0.05		0.05	
lag1_logAge	-0.8881		-0.1778	
	0.84		0.97	
lag1_flow	1.5625	***	1.5437	***
	0.00		0.00	
sector dummy	Yes		Yes	
fund dummy	Yes		Yes	
year dummy	Yes		Yes	
Adjusted R^2	0.51		0.52	
observation	16006		16006	

Table 8
Simultaneous equations of monthly flows on rank gap

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variables are monthly fund flows in the first, second, and third month of the quarter and are measured in millions of U.S. dollars. WD is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. We rank funds based on quarterly return in ascending order into quintiles and group the three middle quintiles together. quarter_q234 and quarter_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile, respectively. Similarly, year_r_q234 and year_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile when funds are ranked based on annual return. logTNA is the logarithm of (1+ total net assets). Load is the total front-end, deterred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). Flow is monthly fund flows measured in millions of U.S. dollars. All control variables are lagged for one period. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	1st-month flow		2nd-month flow		3rd-month flow	
lag1_WD	0.0075		0.0031		-0.0493	**
	0.75		0.90		0.028	
lag2_WD	-0.0452	**	-0.0664	***	-0.0414	**
	0.02		0.00		0.02	
lag1_quarter_r_q234	2.7932	**	2.1992		1.1004	
	0.04		0.11		0.39	
lag1_quarter_r_q5	4.6910	***	6.9297	***	3.2723	*
	0.01		0.00		0.07	
lag1_logTNA	1.1579	***	0.6698	**	0.3839	
	0.00		0.05		0.23	
lag1_load	0.2245		-0.1505		-0.0390	
	0.31		0.50		0.85	
lag1_expense	-1.1141		2.3249	*	2.0032	
	0.39		0.08		0.11	
lag1_turnover	-0.0028		0.0056		-0.0117	*
	0.66		0.39		0.06	
lag1_logAge	-0.0517		-1.3907	**	-1.1219	*
	0.94		0.05		0.10	
lag1_flow	0.9981	***	0.5501	***	0.6545	***
	0.00		0.00		0.00	
sector dummy	Yes		Yes		Yes	
fund dummy	Yes		Yes		Yes	
year dummy	Yes		Yes		Yes	
Adjusted R^2	0.22		0.16		0.36	
observation	16006		16006		16006	

Table 9
Simultaneous equations of monthly flows on rank gap dummy

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variables are monthly fund flows in the first, second, and third month of the quarter and are measured in millions of U.S. dollars. WD_dummy equals 1 when WD is larger than zero and zero otherwise. WD is the rank gap measure for window-dressing defined as:

$$PerformanceRank - \frac{WinnerRank + LoserRank}{2}$$

where PerformanceRank is the percentile rank of fund performance, WinnerRank is the percentile rank of winner proportion, and LoserRank is the percentile rank of loser proportion. We rank funds based on quarterly return in ascending order into quintiles and group the three middle quintiles together. quarter_q234 and quarter_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile, respectively. Similarly, year_r_q234 and year_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile when funds are ranked based on annual return. logTNA is the logarithm of (1+ total net assets). Load is the total front-end, deferred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. All control variables are lagged for one period. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	1st-month flow		2nd-month flow		3rd-month flow	
lag1_WD_dummy	-1.3604		-1.4991		-2.8179	***
	0.23		0.19		0.01	
lag2_WD_dummy	-3.1213	***	-2.5767	***	-1.6497	*
	0.00		0.01		0.07	
lag1_quarter_r_q234	1.9083		1.4753		1.1278	
	0.14		0.26		0.36	
lag1_quarter_r_q5	3.0210	*	5.5812	***	3.3745	**
	0.09		0.00		0.05	
lag1_logTNA	1.1362	***	0.6762	**	0.3883	
	0.00		0.04		0.22	
lag1_load	0.2273		-0.1498		-0.0341	
	0.31		0.50		0.87	
lag1_expense	-1.0001		2.3602	*	1.9693	
	0.44		0.07		0.11	
lag1_turnover	-0.0023		0.0051		-0.0132	**
	0.72		0.43		0.03	
lag1_logAge	0.0279		-1.3811	**	-1.1325	*
	0.97		0.05		0.09	
lag1_flow	0.9961	***	0.5501	***	0.6545	***
	0.00		0.00		0.00	
sector dummy	Yes		Yes		Yes	
fund dummy	Yes		Yes		Yes	
year dummy	Yes		Yes		Yes	
Adjusted R^2	0.22		0.16		0.35	
observation	16006		16006		16006	

Table 10
Simultaneous equations of monthly flows on return gap

The sample includes 27,286 quarterly reports from 2,336 funds that cover the time period from March 1980 through December 2005. The dependent variables are monthly fund flows in the first, second, and third month of the quarter and are measured in millions of U.S. dollars. return_gap is the difference between the realized fund return and the return of a portfolio that invests in the disclosed fund holdings from the beginning of the quarter-ending month. We rank funds based on quarterly return in ascending order into quintiles and group the three middle quintiles together. quarter_q234 and quarter_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile, respectively. Similarly, year_r_q234 and year_r_q5 are dummies for funds located in the middle quintiles and the fifth quintile when funds are ranked based on annual return. logTNA is the logarithm of (1+ total net assets). Load is the total front-end, deterred and rear-end charges. Expense is the expense ratio. Turnover is the annual asset turnover of the fund. LogAge is the logarithm of (1+ age). Flow is the quarterly fund flows measured in millions of U.S. dollars. All control variables are lagged for one period. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	1st-month flow		2nd-month flow		3rd-month flow	
lag1_return_gap	0.3441	**	-0.0806		0.1951	
	0.04		0.69		0.263	
lag2_return_gap	0.0831		0.3573	*	0.3957	**
	0.61		0.06		0.02	
lag1_quarter_r_q234	2.1817	**	3.1901	***	3.4012	***
	0.02		0.00		0.00	
lag1_quarter_r_q5	4.5720	***	5.5983	***	8.7509	***
	0.00		0.00		0.00	
lag1_logTNA	1.2970	***	0.4533		0.5536	**
	0.00		0.11		0.03	
lag1_load	-0.0134		-0.1669		0.0473	
	0.94		0.38		0.78	
lag1_expense	-0.5683		1.2621		1.7732	*
	0.54		0.25		0.07	
lag1_turnover	0.0008		-0.0021		-0.0112	**
	0.86		0.70		0.02	
lag1_logAge	-0.1594		-0.8966		-2.1764	***
	0.75		0.13		0.00	
lag1_flow	0.8956	***	0.5358	***	0.4626	***
	0.00		0.00		0.00	
sector dummy	Yes		Yes		Yes	
fund dummy	Yes		Yes		Yes	
year dummy	Yes		Yes		Yes	
Adjusted R^2	0.23		0.12		0.22	
observation	24967		24967		24967	

Table 11
J-test result

This table presents the J-test results of the monthly flow regression model using the rank gap measure vs. regression model using the return gap measure. First, we estimate a regression model of flows in the third month of the quarter on the rank gap measure and calculate the set of fitted value for the dependent variable. Then, we estimate a regression model of the third-month flows on the return gap measure and calculate the set of fitted value for the dependent variable. Next, we estimate the rank gap model again, but also using the fitted value obtained from the return gap model as an added explanatory variable. We also estimate the return gap model again, but also using the fitted value obtained from the rank gap model as an added explanatory variable. We present the coefficient of the added fitted value. p-value is reported under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

variable	rank gap model	return gap model
fitted value from return gap model	0.0465	
	0.97	
fitted value from rank gap model		1.0112 ***
		0.01

A Life Cycle Analysis of Performance and Growth in U.S. Mutual Funds

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This version: June 3, 2008

Abstract

I propose a five-stage growth model to describe the life cycle evolution of mutual funds and show that mutual funds exhibit distinctive performance, size, expense ratios, asset turnover, and other pertinent characteristics through stages of incubation, high-growth, low-growth, maturity, and decline. I also investigate the viability of managerial strategies to affect a fund's life cycle evolution and find that changing a declining fund's investment objective is effective in rejuvenating asset growth and thus repositioning the fund to younger life cycle stages. However, the strategy of adding portfolio managers appears to have no such rejuvenation effect.

JEL Classification: G11; G20; L2; L22

Keywords: Mutual funds; Life cycle; Economies of scale; Managerial behavior; Growth

* I am grateful to my dissertation committee members, Gerald D. Gay (co-chair), Jason T. Greene (co-chair), Conrad S. Ciccotello, and Harley E. Ryan for their invaluable advice and continued support. I thank Vikas Agarwal, Marcin Kacperczyk, Jayant Kale, Jason Karceski, Yee Cheng Loon, Reza S. Mahani, Jame E. Owers, Laura Starks, Ling Ling Wang, and seminar participants at Georgia State University, University of Wisconsin at Whitewater, Bryant University, State University of New York at Albany, Slippery Rock University, Georgia College & State University, and the 2007 Financial Management Association Conference for their helpful comments and suggestions. Any errors that remain are mine. Contact information: Department of Finance, J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303-3083. Tel.: 1-404-413-7314; Fax: 1-404-413-7312. E-mail address: lling1@gsu.edu.

1. Introduction

The aim of this study is to examine the mutual fund industry using a life cycle framework for purpose of investigating whether fund's life cycle is systematically associated with observed variations in performance, flows, strategies, and other key fund characteristics. The industrial organization literature proposes a variety of models to describe the life cycle evolution of firms. Empirical evidence shows that industrial firms indeed exhibit distinctive characteristics in terms of operating performance, strategy, organizational structure, and decision-making style as they progress through different life cycle stages.[8] Mutual funds and industrial firms, as two different types of corporate organization, share a number of common characteristics. They are both economic entities engaged in commercial or industrial enterprise with a goal of maximizing the wealth of owners and shareholders. More importantly, these firms exhibit difficulty in the reversibility of their life cycle paths due to prior investment in branding and marketing as well as human capital investment in strategy specific skills. Drawing upon the prior literature, I propose a mutual fund life cycle model that encompasses stages of incubation, high growth, low growth, maturity, and decline. A life cycle stage is defined as a time period associated with a common configuration of variables including asset growth, size, expense ratios, and other pertinent characteristics. Within this life cycle framework, I study the dynamics in fund performance, net flows, and other pertinent characteristics. In addition, I investigate the viability of rejuvenation strategies to reposition a fund to younger life cycle stages, particularly when the fund is in the stage of decline.

[8] Quinn and Cameron (1980) and Miller and Friesen (1984) provide a literature review on various firm life cycle models. More recently, Diamond (1991), Berger and Udell (1998), and Bulan and Yan (2007) study the financing behavior of industrial firms over their life cycle. Fama and French (2001), Grullen, Michaely and Swaminathan (2002), DeAngelo, DeAngelo and Stulz (2005), Bulan, Subramanian, and Tanlu (2007) find that mature firms are more likely to initiate or increase dividend payout. Anthony and Ramesh (1992) and Dickinson (2007) show that a firm's profitability and growth are functions of its life cycle stage. Liu (2008) provides evidence that accruals decline as a firm becomes mature. There are numerous studies on bank life cycle including Hunter and Srinivasan (1990), DeYoung and Hasan (1998), Goldberg and White (1998), DeYoung (1998), and DeYoung, Goldberg, and White (1999).

Prior studies have typically addressed the explanation of observed variations in fund performance from a static perspective. That is, the influence of factors such as age and size is typically modeled as being constant over a fund's lifespan. In practice, the interactions between factors could be dynamic over time as mutual funds correspondingly align their internal attributes such as investment strategy, fund structure, and managerial characteristics to changes in external factors such as operating environment, market movements, and technology. Thus, the application of the life cycle concept to mutual funds could provide an alternative perspective for identifying potential dynamic relations.

Specifically, I seek to address two main research questions. First, do mutual funds have life cycle stages associated with different fund characteristics? The industrial organization literature argues that firms become more mature because of a diminishing investment opportunity set. Studies of mutual funds such as Chen, Hong, Huang, and Kubik (2002) and Berk and Green (2004) demonstrate that growth in fund assets will lead to poorer fund performance. Based on these studies, I argue that a mutual fund's life cycle evolution is driven by the relative size of its investment opportunity set, which depends on fund size, managers' skills, and the investment opportunities available in the market. Other things being equal, the relative size of the investment opportunity set decreases when a fund's total net assets increase. Faced with fewer investment opportunities, fund managers are likely to experience declining performance, which in turn will likely lead to decreasing net fund flows. Thus, we expect to observe a declining asset growth as a mutual fund descends into older life cycle stages.

The second research question investigates whether strategies are available that fund families can pursue to reposition funds to younger stages in their life cycle. I examine two alternative strategies, changing the investment objectives or hiring more portfolio managers. These two strategies could enhance a fund's capability to identify additional investment opportunities and therefore improve performance and retain fund growth. This investigation could provide some insights into how fund families strategically affect a fund's operation and growth.

My sample consists of 2,730 U.S. open-end mutual funds that cover the time period from January 1961 through December 2005. I construct a composite score measure to classify each fund's life cycle stages, using a fund's age and its one-year and three-year moving average growth rates. Exploring the explanatory power of alternative life cycle stage measures on the variations of monthly fund returns, I find that the composite score measure provides information beyond that contained in fund age.

I perform both univariate and multivariate analysis on fund performance over life cycle stages. The results indicate that the life cycle effect on fund performance is both economically and statistically significant, with the magnitude monotonically increasing over life cycle stages. When a fund develops from the high-growth to low-growth stage, its risk-adjusted monthly returns drop by 41 basis points. When it reaches the maturity stage, the returns drop by 10 more basis points. The returns drop again by 29 basis points when the fund descends to the stage of decline. In addition, net monthly returns and S&P500 excess returns monotonically decrease over life cycle stages, too. These findings are consistent with the proposed mutual fund life cycle model in that mutual funds experience poorer performance across stages of their life cycle. I also find that monthly net fund flows decline monotonically after the high-growth stage. Furthermore, there are inter-stage differences in total net assets, expense ratios, asset turnover, and the number of stock held in the portfolio.

My empirical findings shed light on economies of scale in the mutual fund industry. Earlier studies model the effect of size being constant over a fund's life cycle and find that an increase in fund size leads to poorer fund performance. I extend these studies by investigating the scale effect over a fund's life cycle stages. The empirical evidence indicates that a marginal increase in size significantly affects fund performance at the high-growth stage when average fund size is relatively small. In the case of a $10 million increase in total net assets, the risk-adjusted monthly returns will drop by 13 basis points. After the fund descends into older stages, however, the marginal effect of size becomes economically smaller.

Finally, I investigate the effectiveness of alternative strategies that fund families have pursued to rejuvenate fund growth. I compare the one-year stage transition matrices of the funds that neither changed investment objectives nor hired more portfolio managers with those that hired more managers and those that changed investment objectives. The stage transition probabilities show that when a fund is in the decline stage, a change of its investment objective could rejuvenate fund growth and in the next year reposition the fund to an younger life cycle stage. Hiring more portfolio managers, however, seems not effective as a way to rejuvenate fund growth. I also estimate a multinomial logistic regression model of stage transition to further explore these two strategies. The regression results support the findings of univariate analysis. Investigating the rejuvenation effect of changing fund's investment style at different life cycle stages, my study extends the work by Brown and Goetzman (1993) who find that changing a fund's investment style generally lowers performance relative to its peers in the same fund sector.

This paper proceeds as follows. Section 2 proposes a five-stage mutual fund life cycle model. Section 3 develops the hypotheses. Section 4 addresses the data and reports the descriptive statistics. Section 5 presents the results of multivariate analysis on the relation between fund performance and life cycle stages. Section 6 investigates the effectiveness of alternative strategies that fund families have pursued to rejuvenate fund growth. Section 7 presents the robustness tests and Section 8 concludes the paper.

2. Mutual fund life cycle model

In this section, I propose a five-stage growth model to describe the life cycle evolution of mutual funds.

2.1. Incubation stage

Fund families open new funds when the potential to generate additional fee income is substantial (see, Khorana and Servaes, 1999). According to Arteaga, Ciccotello and Grant (1998), fund families use two alternative strategies to develop new funds, incubation and selective attention. Under incubation strategy, fund families raise seed money internally to start a number of small funds and run them in private. After running these seed funds for a while, fund families will open those funds with good track records to the public but terminate those poorly performing funds. Under the second approach, fund families launch new funds to the public without an incubation period whereas devote extra attention to the new funds including subsidizing operating expenses and more than a proportional allocation of profitable investment opportunities.

Fund families also determine the characteristics associated with a new fund. Massa (1998, 2003) argues that fund families open a series of funds with various styles and fee structures to exploit investor heterogeneity and increase market share. Nanda, Narayanan, and Warther (2000) develop a model in which managers set the mutual fund fee structures to maximize the captured rent, taking into account the effect on fund flows. Bar, Kempf and Ruenzi (2005) show that the choice of management is a strategic decision made at the fund family level. Fund families also have power over fund governance. As showed by Tufano and Sevick (1997), fund sponsors select a new fund’s initial independent board members who accept high fees from the sponsors and in turn could fail to act in the best interests of fund investors.

2.2. High-growth stage

After opening to the public, new funds generally begin a high-growth phase that is associated with good performance and large fund inflows. Blake and Timmermann (1998) study 2,300 U.K. open-end mutual funds and find evidence that funds weakly outperform their peers during their first year after public offerings. Two factors could contribute to the high returns achieved at the high-growth stage. First, funds at this stage are small. Portfolio managers only invest in the stocks and industries for which they have informational advantages, which bring forth high returns (see, Kacperczyk, Sialm, and Zheng, 2005). Second, fund families subsidize new funds and give them preference in the allocation of resources. For example, Zweig (1996) and Arteaga, Ciccotello and Grant (1998) both mention that new funds obtain preferential allocations of underpriced IPOs. Gaspar, Massa, and Matos (2006) investigate strategic cross-fund subsidization and find that fund families allocate relatively more underpriced IPOs to high fee, high performance, and young funds. Since young funds have relatively small size, a favorable allocation of profitable investment opportunities leads to superior performance.

2.3. Low-growth stage

Funds in the low-growth stage are older and larger than those in the high-growth stage. As a fund's assets grow, the relative size of the investment opportunity set shrinks. The number of stocks held by the fund increases as portfolio managers exhaust good investment opportunities for which they know the best and increase investment in other stocks with which they are less familiar. As a result, a fund's returns are relatively lower than those received at its high-growth stage. Consequently, net flows decrease.

2.4. Maturity stage

The increasing complexity of the investment task from growing assets leads to increasing transaction costs because of the lessened flexibility that comes with holding larger positions (see, e.g., Perold and Salomon, 1991; Beckers and Vaughan, 2001; Pollet and Wilson, 2007; Edelen, Evans, and Kadlec, 2007). As managers continue to invest in those identified good opportunities (undervalued stocks), large amounts of accumulated purchasing of the same stocks will push upward prices and thus lower the expected returns. Wermers (2003) find strong evidence that flow-related additions to existing positions push up stock prices, especially among growth-oriented funds. Prior studies also find that the aggregate purchase of the same stock by many funds will increase the price of the stock. Hong, Kubik and Stein (2005) show that a fund manager is more likely to buy or sell a particular stock if other managers in the same city are buying or selling that stock. Wermers (1999) find empirical evidence that mutual fund herding speeds up the incorporation of new information in stock prices.

A manager's incentive to retain and attract assets under management contributes to poorer fund performance over life cycle stages of the fund. Jensen's (1986) free cash flow theory suggests that managers of industrial firms with large free cash flows are more likely to diversify in value-destroying projects after they exhaust all investment opportunities. This is analogous to the mutual fund industry. Because the management fee is a percentage of the total assets under management, managers have a propensity for over-investment and begin to adopt passive investment strategies when they have exhausted all lucrative investment opportunities with a large amount of "free" money at hand. Chen, Hong, Huang, and Kubik (2002) and Berk and Green (2004) argue that managers invest a larger portion of fund assets in benchmark portfolios as funds grow. Chen et al. (2002) further argue that the rationale behind this behavior is that managers no longer care about maximizing fund returns after funds reach a certain size. A potential explanation for managers' losing interest in maximizing returns is that managers realize that they are unable to find more profitable investment opportunities.

Funds obtain lower average returns in the maturity stage than in the low-growth stage because of larger trading costs, declining-profit opportunities, and overinvestment. As a result, the average fund inflows are lower than they were in the growth stages but fund outflows are higher. Some funds chose to close to avoid these scale diseconomies. Nevertheless, earlier studies find that closing a fund does not protect its performance in the next period (see, Zhao, 2004; Bris, Gulen, Kadiyala, and Rau, 2007). One possible explanation for their findings is that fund size is already too large when the fund was closed.

2.5. Decline stage

Because of large trading costs, absence of profitable opportunities, and severe overinvestment, mutual funds at the stage of decline experience extremely poor performance and large cash outflows. Fund families have incentives to create and market “star” funds but eliminate poorly performing funds, and thus they are likely to terminate small funds with declining returns.[9]

2.6. A general descending life cycle path

Industrial firms can not readily reverse the evolution process without incurring significant costs. The reason for this difficulty in reversibility is that many expenditures and investments are at least partly irreversible. For example, the expenditure in marketing a particular product is irreversible. The firm will lose the brand value of the old product if it totally changes its product line. A project can be firm specific and therefore it can not be sold to a different firm at a price that fully covers investment. Furthermore, executives’ experience and skill is often restricted to some specific areas. A firm could lose the value of investment in human capital if it changes its operating strategy. Thus, once some expenditure or investment is made, a firm either cannot return to the previous state immediately or would incur some costs in doing so (see, Baldwin, 1982; Pindyck, 1988, 1991).

Like the counterpart of an industrial firm, a mutual fund’s life cycle evolution path is also not readily reversible because of the investments in marketing and human capital. As the relative investment opportunity set shrinks over a fund’s life cycle stages, it becomes harder for fund managers to find profitable opportunities to support continued growth. Although managers could identify additional investment opportunities through some strategies such as changing their investment strategies or objectives, such changes are constrained by a fund’s prospectus and a change in investment objective requires the approval of the majority of fund holders.[10]

[9] For a discussion of mutual fund exit strategy such as merger and liquidation, see Jayaraman, Khorana, and Nelling (2002), Zhao (2005), and Ding (2006).

[10] The Investment Company Act of 1940 Section 13(a) states “No registered investment company shall, unless authorized by the vote of a majority of its outstanding voting securities…deviate from its policy in respect of concentration of investments in any particular industry or group of industries as recited in its registration statement, deviate from any investment policy which is changeable only if authorized by shareholder vote, or deviate from any policy recited in its registration statement pursuant to section 8(b)(3)…”

Furthermore, changing a fund's investment objective will entail other significant costs. First, a fund has invested in marketing and advertising with respect to the declared objective. If the fund changes its investment objective, its brand value associated with the old objective will vanish. Second, a portfolio manager's experience and skill could be strategy or style specific. His expertise may not be readily transferable if the fund changes its investment objective. Therefore, mutual funds evolve into their older life cycle stages in a general descending manner, and they would incur significant costs to return to younger stages.

3. Hypothesis Development

Funds in early stages of their life cycle are usually small. Managers do not have enough money to fully exploit all of the good investment opportunities they can identify, and thus invest in the best investment opportunities with the highest expected returns. Therefore, mutual funds achieve supreme performance in their early stages. As funds grow up, managers exhaust their best investment opportunities and thus have to invest in the second-best and thereafter declining-profit opportunities. The average return decreases accordingly, and the growth rate declines. Eventually, managers have exhausted all investment opportunities. As a result, performance is poor leading to net fund outflows. In the stage of decline, managers have to overinvest and adopt a passive investment strategy, which gives rise to much lower returns followed by larger amount of net cash outflows. Based on this reasoning, I posit that older life cycle stages are associated with poorer fund performance.

Prior studies such as Chen et al. (2002) find that an increase in size leads to lower fund performance. These studies model the marginal effect of size as being constant over a fund's life cycle. However, this assumption could be skeptical because funds vary in size over their life cycle and thus the same amount of increase in assets on a larger base should have a smaller effect on performance. The mutual fund life cycle model predicts that fund size is relatively small in the high-growth stage, but larger in older stages. Therefore, I expect that the marginal effect of size is stronger in the high-growth stage, but weaker in older stages.

When a fund reaches older stages in its life cycle, performance becomes poorer and asset growth declines. Fund families have high incentives to reboot fund growth because the management and advisor fee is a percentage of the assets under management. Canals (2001) argues that "… managers should look at corporate growth from a dual perspective: the internal dimension of resources and capabilities and the external dimension of markets and customers." To obtain growth from the external dimension of markets and customers, fund families seek to attract more fund inflows by pursuing strategies such as increasing advertising, reducing fees, and creating multiple share classes. Prior studies such as Sirri and Tufano (1996), Jain and Wu (2000), and Barber, Odean, and Zheng (2005) find that increasing marketing expenses can attract more fund inflows. Christoffersen (2001) find evidence that poorly performing funds waive fees to adjust net returns to investors. As described in Nanda, Wang, and Zheng (2005), mutual funds tend to create multiple share classes to attract more investors with different preferences for fee structure.

This paper focuses on the internal dimension of growth: resources and capabilities. Fund families can pursue some strategies to increase the fund's resources and also enhance its capabilities to identify additional investment opportunities. One potential strategy is to hire more portfolio managers, a step that could help generate more investment ideas. Another potential strategy is to change the investment objective. By changing a fund's investment objective, managers could have an expanded investment opportunity set and more flexibility in choosing stocks. I hypothesize that these two strategies can improve fund performance and thus reposition funds to their younger life cycle stages.

4. Data description

4.1. Data sources

Several sources are employed to create the main data set by merging the survivorship-bias-free mutual fund database from the Center for Research in Security Prices (CRSP) with the Thomson Financial mutual fund holding database and the CRSP stock database. The CRSP mutual fund database includes information on mutual fund monthly returns, total net assets (TNA), inception dates, fee structure, fund investment objectives, asset turnover ratios, managers' names (begins 1992), management company names (begins 1993), and other fund characteristics. The Thomson Financial mutual fund database provides quarterly or semiannual reported stockholdings of U.S. mutual funds. I merge these two databases using MFLINKS from Wharton Research Data Services (WRDS). I link each stock in the portfolios to the CRSP stock database to find its industry classification code (SIC). Less than 0.67% of all holding-stock observations lack a SIC code. The number of distinct four-digit SIC code in a given portfolio is used as a proxy for industry concentration. Because one fund could have multiple share classes, I compute the total net assets of a fund as the summation of the total net assets in each share class. Weighting each share class by its total net assets, I obtain the value-weighted averages of monthly net returns, expense ratios, asset turnover ratios, and fee structures at the fund level.

To be included in the sample, several criteria are employed. First, each fund in the sample must have operated for at least three years.[11] Second, I eliminate the balanced, bond, index, international, and sector funds because I focus on actively managed equity funds that invest mainly in the U.S. stock market. I used the Wiesenberger (WI) fund type code, the ICDI fund objective code, and Standard & Poor's detailed objective code to categorize funds as Growth fund, Growth and Income fund, and Income fund, as described in Appendix A. My final sample of

[11] Funds with a history that is shorter than three years are less likely to experience distinctive life cycle stages.

2,730 mutual funds covers the period from January 1961 to December 2005, and fund holding data covers the period from January 1980 to December 2005.

In addition to reported monthly returns, I examine S&P500 excess returns and abnormal returns adjusted by Carhart's (1997) four factors. I employ time series regression with Carhart (1997) four-factor model to calculate loadings on different risk factors, using lagged 24 monthly returns. Using these risk loadings, I obtain risk-adjusted returns for the next period. I construct several control variables. LogTNA is the natural logarithm of one plus total net assets. LogFamily is the natural logarithm of one plus the size of the family the fund belongs to. Age is the number of years since the inception of the mutual fund. Total load is the total front-end, deferred, and rear-end load charged by the fund. Flows are monthly net fund flows into the mutual fund divided by its total net assets. It equals $[TNA_t - TNA_{t-1} \cdot (1+r_t)]/TNA_t$, where r_t is the net return at month t. Industry Number is the number of the distinct four-digit SIC code in the portfolio. Stock Number is the number of all domestic stocks in the portfolio. Manager Number captures the number of portfolio managers running the fund. For those funds listed as "team," "committee," or "multiple," I follow Chen et al. (2002) and set the manager number to four. Thus, Manager Number takes on a value of one, two, three, or four.

4.2. Life cycle stage measure

Using a good instrument for a mutual fund's life cycle is critical in empirical research. Prior studies usually treat fund age as a proxy for a fund's life cycle. The validity of age as a good life cycle proxy, however, is questionable. According to Churchill and Lewis (1983), the age of an organization alone is unlikely to provide a valid reflection of its life cycle stages. Using age to proxy a fund's life cycle implicitly assumes that all funds have the same speed of development, which is unreasonable. For example, at age 10, Fund A reaches $100 million in size and experiences low returns and thus low growth because its manager has exhausted all investment opportunities. In contrast, at age 10, Fund B reaches $100 million and still achieves high returns and thus high growth because its manager is more skilled than Fund A's manager in finding good investment opportunities. Obviously, the two funds of the same age have different relative size of opportunity set and accordingly locate in different stages of their life cycle. Therefore, using age as a life cycle proxy can mix the information provided by funds that locate in different stages. Another disadvantage of using age is that it is hard to determine which age corresponds to which life cycle stage without additional information provided by other variables. Similarly, two funds of the same size can be in different life cycle stages if they have different relative size of investment opportunity set. Therefore, size per se fails as a good life cycle proxy, too.

I construct a composite score measure to classify a fund's life cycle stages, using fund age and its one-year and three-year moving average growth rates. The mutual fund life cycle model predicts that a fund experiences decreasing asset growth over stages of its life cycle, and therefore a fund's growth rate includes some information on the relative size of the investment opportunity set and corresponding life cycle stages. I adjust a fund's annual growth rate by annual market return to exclude the influence of market movement on fund value, and use the three-year moving average growth rate to smooth the evolution process.[12] Then, I rank all fund-year observations in ascending order into four quartiles based on age, growth, and moving average growth, respectively.

Next, I match each fund-year observation in terms of the three variables mentioned above to the cells in the table illustrated in Appendix B. Any matching cell will gain one point and other cells gain zero. I sum all points within the same stage column to obtain a composite score for each stage. The stage column that scores highest will assign the corresponding life cycle stage to the given fund year. In a case in which three stages have the same highest score, I choose the stage in the middle. I do not empirically study the incubation stage because of the lack of data.

[12] Provided by CRSP, this market return is a value-weighted return of a portfolio of all stocks in the NYSE, Amex, and Nasdaq. Adjusting annual growth rate by the mean return of all funds in the same fund sector produces very close results.

4.3. Descriptive statistics

After using the composite-score measure to classify a fund's life cycle stages for all fund-years, for each fund age I calculate the percentage of funds located in the life cycle stages of high-growth, low-growth, maturity, and decline, respectively. As a result, I obtain four age-series of fund percentage as demonstrated in Fig. 1. The graph shows that, in general, funds locate in the high-growth stage when they are young and progress to older life cycle stages as they age. However, old funds do not all stay at the stage of maturity or decline. For funds that are 30 years old, about 3% locate in the high-growth stage, 12% in the low-growth stage, 36% in the maturity stage, and only 49% in the stage of decline. These findings suggest that age is not a good proxy for life cycle stages.

I also explore the stage transition matrices presented in Table 1 to gain more insight into the process of mutual fund life cycle evolution. P1, P4, and P9, respectively, indicate the stage transition matrices in the second, fifth, and tenth year. For funds that locate in the high-growth stage, 37% remain in the same stage in the next year, 41% drop to the low-growth stage, 16% descend to the maturity stage, and only 6% devolve to the decline stage. After four years, only 17% of the funds remain in the high-growth stage, 36% fall to the low-growth stage, 31% reach the maturity stage, and 15% devolve to the stage of decline. After nine years, only 7% of the funds remain in the high-growth stage, 22% descend to the low-growth stage, 38% devolve to the maturity stage, and 32% drop to the decline stage. These stage transition patterns indicate that funds progress smoothly from young to older life cycle stages, which is consistent with the findings in Fig. 1.

Table 1 also indicates that declining funds do not necessarily stay forever in the decline stage. Some of the declining funds rejuvenated and repositioned to younger life cycle stages. The percentage of declining funds that remain in the decline stage after one year is 68%. This number drops to 52% after four years and 41% after nine years. This evidence suggests that, like industrial firms, declining funds can revive.

Table 2 presents the descriptive statistics of sample funds in each life cycle stage. All variables are winsorized at one and the 99th percentile.[13] I observe that the distributions of some variables are highly skewed. For example, the mean of TNA in the high-growth stage is $283 million, but the median is only $71 million. In other stages the means of TNA are much higher than the medians, too. Therefore, I focus on medians in the following analysis. Net monthly returns, S&P500 excess returns, and four-factor adjusted returns are all monotonically decreasing over life cycle stages, as demonstrated in Fig. 2. The median test shows that performance shifts between stages are statistically significant at the 1% level. Chevalier and Ellison (1997) and Bar, Kempf, and Ruenzi (2005) find that young funds are more likely than old funds to take high risk. Managers of young funds may invest in stocks with high systematic risk, which could result in the observed higher total return in earlier life cycle stages. The risk-taking behavior of fund managers, however, cannot explain the monotonically decreasing four-factor adjusted returns. The decreasing risk-adjusted return over stages is much more consistent with the hypothesis that funds progress through their life cycle paths with a diminishing investment opportunity set.

Table 2 also indicates that mutual funds charge different expenses ratios in different life cycle stages. The median expense ratios vary from 1.37% in the high-growth stage to 1.22 % in the low-growth stage, 1.17% in the maturity stage, and 1.28% in the stage of decline. The median test shows that the changes in expense ratios between stages are statistically significant. This finding is consistent with prior studies in that expense ratios decrease with fund size (see, Malhotra and McLeod, 1997; Lazko, 1999; Rea, Reid, and Millar, 1999; LaPlante, 2001; Warner and Wu, 2006).[14]

[13] The multivariate analyses produce very similar results when variables are winsorized at 5 and the 95th percentile.
[14] Dermine and Roller (1992) study 137 French mutual funds and find that expense ratio decreases and then increases as fund size becomes larger.

The annual asset turnover ratios decrease over the high-growth, low-growth and maturity stages. This pattern implies that larger fund size leads to less flexibility in changing holding positions, and hence managers have less incentive to trade. However, in the decline stage the asset turnover jumps to 0.77, which is higher than in the high-growth stage. Given the fact that fund size in the decline stage is larger than it is in the high-growth stage, the higher turnover ratio in the decline stage suggests that managers trade more frequently than they do in other stages. Another reason for this high asset turnover could be that managers have to sell their holdings because of a large amount of redemption. Fig. 3 shows the dynamics of turnover ratios over life cycle stages.

Fig. 4 illustrates another finding from Table 2 that monthly net fund flows monotonically decrease over life cycle stages. In the low-growth stage, funds achieve positive S&P500 access returns but negative four-factor adjusted returns. However, investors respond with positive net fund flows. This evidence suggests that some fund investors do not use risk-adjusted returns to evaluate fund performance, which is consistent with the findings in Gruber (1996), Sirri and Tufano (1998), and Del Guercio and Tkac (2002).

I also observe from Table 2 that the number of stocks and the number of industry in portfolio shift between life cycle stages. Median tests show that almost all of these shifts are statistically significant. Both stock number and industry number increase from the high-growth to low-growth stage but decrease after the maturity stage although the size at the maturity stage is larger than that at the low-growth stage. This finding is not inconsistent with the hypothesis that managers are constrained by the size of the fund, other things being equal. My explanation is that the investment opportunity set is dynamic. For example, when a fund is at the low growth stage the identified investment opportunities locate in 50 stocks. As time goes by, fund size increases. Nevertheless, the manager focuses his investments in only 40 stocks because the market changed and thus he can not find more good investment opportunities. So, the number of stock in portfolio could drop even if fund size increases.

Table 3 presents correlations between main variables.

4.4. Life cycle effect vs. scale effect

Although Table 2 indicates that average fund size increases from the high-growth to maturity stage and that size in the decline stage is much larger than in the high-growth stage, it is premature to conclude that the increasing scale of size is the only reason for the decreasing performance over stages observed in Fig. 2. In the mutual fund life cycle model, the declining performance over stages is driven by the decreasing relative size of the investment opportunity set, which depends on fund size, managerial skills, and the opportunities available in the market. The increasing scale cannot fully explain the life cycle effect on performance.

To distinguish scale effect from life cycle effect, I conduct the following data mining. Within each life cycle stage, I rank fund-month observations by size into quartiles, with the fourth quartile having the largest size. Next, I choose the fourth quartile in the high-growth stage, the third quartile in the low-growth stage, and the second quartile in both the maturity and decline stages so that the average size of the sample funds decreases over stages. Finally I calculate the medians and means of monthly returns of these chosen quartiles and report the results in Table 4.

I observe that all three measures of fund performance monotonically decrease over the chosen quartiles. Because average fund size of the chosen quartiles monotonically declines, the scale effect is not responsible for the poorer performance over life cycle stages. This finding suggests that, in addition to scale, there are other factors that lead to declining performance over stages.

5. Mutual fund performance and life cycle stages

5.1. Regression of four-factor adjusted returns

I estimate pooled OLS, random effect, and fixed effect panel regression models to further investigate the relation between fund performance and life cycle stages. I regress monthly four-factor adjusted returns on dummies of life cycle stages, fund size, the interactions of stage dummies with fund size, and other fund characteristics. The variables of life cycle stage are lagged for one year while other independent variables are lagged for one month. Following Petersen (2007), I correct for the fund effect and the time effect in the pooled OLS regression. The regression specification is

$$\begin{aligned} R_{i,t} &= \alpha + \sum_{k=2}^{4} D_k LifeCycle_{i,t-1,k} + \beta_1 LogTNA_{i,t-1} \\ &\quad + \sum_{k=2}^{4} \delta_k LogTNA_{i,t-1} \times LifeCycle_{i,t-1,k} + \gamma \mathrm{X}_{i,t-1} + \varepsilon_{i,t}\ , \end{aligned} \tag{1}$$

where R is the four-factor adjusted return; LogTNA is the natural logarithm of one plus TNA; $LifeCycle_k$ consists of three dummy variables that indicate the low-growth, maturity, and decline stages; **X** is a set of control variables that includes asset turnover, expense ratios, total loads, fund flows, and dummies of fund sectors. Table 5 presents the regression results.

In Model 1, the coefficients of LowGrowth, Maturity, and Decline are -40.64, -51.31, and -80.37, respectively. The Wald test shows that these coefficients are statistically different from each other at the 1% level. These findings indicate that the life cycle effect on fund performance is monotonically increasing across stages. The observed increasing life cycle effect is consistent with my mutual fund life cycle model in that when a fund develops over life cycle stages, the relative size of the investment opportunity set shrinks and thus performance declines. Since I include fund size in the regression specification, the observed life cycle effect is not likely driven by the scale. The random effect and fixed effect regression models produce consistent results.

Next, I examine the interactions between fund size and life cycle stages. The results of OLS regression indicate that, in the high-growth stage (as the reference group), fund size has a negative effect on performance and is statistically significant at the 1% level. For a $10 million increase in size, the four-factor adjusted monthly return will decrease by about 13 basis points.[15] Wald test cannot rejects the null that the sum of the coefficient of LogTNA and the coefficient of LogTNA*LowGrowth equals zero, or the null that the sum of the coefficient of LogTNA and the coefficient of LogTNA*Maturity equals zero. On the other hand, Wald test reject the null that the sum of the coefficient of LogTNA and the coefficient of LogTNA*Decline equals zero. However, I can not conclude that the size effect is positive at the stage of decline because of the inconsistent statistics in both random effect and fixed effect models. For random effect specification, Wald test reject the null that the sum of the coefficient of LogTNA and the coefficient of LogTNA*LowGrowth equals zero and the null that the sum of the coefficient of LogTNA and the coefficient of LogTNA*Maturity equals zero. However, the test cannot reject the null that the sum of the coefficient of LogTNA and the coefficient of LogTNA*Decline equals zero， which suggests that future performance is not related to fund size at the decline stage. Since declining funds experience negative net fund flows, this evidence is consistent with the finding in Bris et al. (2007) that there is not a negative relation between size and four-factor α when funds experience low net fund flows. The results of the fixed effect panel regression imply a decaying scale effect across the four stages. Overall, I find solid evidence that the marginal effect of size is larger in the high-growth than in older life cycle stages.

5.2. Composite score measure vs. age measure

In this section I investigate whether my composite score measure is better than fund age to proxy for mutual fund life cycle. I construct another life cycle measure using age alone. I rank all fund-year observations by age in ascending order into four quartiles, with the first quartile having the youngest age. Fund years at the first quartile are assigned to the high-growth stage, while those at the fourth quartile are assigned to the decline stage. Table 6 presents the results of

[15] The marginal effect = (-5.404) x Log(1+10) = -13.

regression of monthly returns on life cycle stages classified with alternative life cycle stage measures.

In Model 1 where the composite-score measure is used, the coefficients of fund size, life cycle stages and interactions between size and life cycle stages are all statistically significant at the 1% level. In Model 2 where the age measure is used, the coefficient of LogTNA and the coefficient of LogTNA*LowGrowth is not even statistically significant at the 10% level. To further explore whether the composite-score measure provides information beyond that contained in the age measure, I conduct the following J-test procedure for testing between the two non-nested regression models.[16]

First, I estimate Model 1 and Model 2 in Table 6 and calculate the sets of fitted values for the dependent variable. Then I estimate a regression specification based on Model 1, but also using the fitted value obtained from Model 2 as an added explanatory variable. I also estimate a regression specification based on Model 2 using the fitted value from Model 1 as an added explanatory variable. The null hypothesis is that the composite score measure provides more information than the age measure and Model 1 fits the data better. The null hypothesis is supported if the estimate of the coefficient of the fitted value from Model 1 is significantly different from zero and the estimate of the coefficient of the fitted value from Model 2 is not significant. If both estimates are significantly different from zero, then each measure provides some information not present in the other and the null is rejected. If both estimates are insignificant, then both measures provide similar information and neither measure is superior to the other. Table 7 presents the J-test results.

For the regression based on Model 2, the coefficient of the fitted value from Model 1 is 1.128 and different from zero at the 1% significance level. For the regression based on Model 1, the coefficient of the fitted value from Model 2 is not statistically different from zero. These

[16] For a discussion of the J-test procedure, see Davidson and MacKinnon (1981) and McAleer (1995).

results suggest that the composite score measure provides information beyond that contained by the age measure.

6. Rejuvenation strategy

In this section, I investigate the effects on life cycle evolution of changing fund investment objectives or hiring more portfolio managers. The sample used includes 2,229 funds covering the time period from 1993 through 2005. In this sample, 908 funds neither changed their investment objectives nor hired more managers within the time period. Among the 287 events of changing objectives, I use 268 events that have second-year observations. There are 1,462 incidents of adding managers from which I use 1,357 events that have second-year observations.

6.1. Stage transition matrices

I compare the one-year stage transition matrices of funds that neither changed their investment objectives nor hired more portfolio managers (as a reference group) with those that hired more portfolio managers and those that changed the investment objectives. If these two rejuvenation strategies work, compared with the reference group, funds that changed their investment objectives or hired more managers should in the next year have higher transition probabilities to younger life cycle stages.

Table 8 presents next-year stage transition matrices of funds that neither hired more managers nor changed fund objectives (no-strategy funds in Panel A), those of funds that changed the investment objectives (in Panel B), and those of funds that hired more portfolio managers (in Panel C). Comparing Panel A and Panel B, I find that when funds are in the low-growth stage changing their investment objectives has no effect on the probabilities of transition to younger life cycle stages. When funds are in the maturity stage, however, changing their investment objectives seems to decrease the probability of descending to older life cycle stages. As observed, 12% of the funds in Panel B devolve to older stages in the next year vs. 20% in Panel A. When funds are in the decline stage, changing the investment objectives seems to increase the probability of developing to younger life cycle stages. In the decline stage, totally 33% of the funds in Panel B evolve to younger stages in the next year vs. only 17% in Panel A.

The strategy of hiring more portfolio managers seems not effective in rejuvenating fund growth, as I observe no significant difference in the rejuvenation probabilities between Panel A and Panel C. For funds in the low-growth stage, the rejuvenation probability to the high-growth stage in the next year is 5% in both Panel A and Panel B. For funds in the maturity stage, 10% in Panel C reposition themselves to younger stages in the next year vs. 9% in Panel A. For funds in the stage of decline, 18% in Panel C develop to younger stages in the next year vs. 17% in Panel A.

6.2. Multinomial logistic regressions

I estimate a multinomial logistic regression model to further investigate the effectiveness of the two strategies. The dependent variable has a category value of 0, 1, and 2, respectively, which indicates transition in the next year to the same, younger, or older life cycle stages. The regression specification is

$$\begin{aligned} y_{i,t} &= \alpha + \sum_{k=2}^{4} D_k LifeCycle_{i,t-1,k} \\ &+ \beta_1 Obj_{i,t-1} + \sum_{k=2}^{4} \beta_k Obj_{i,t-1} \times LifeCycle_{i,t-1,k} \\ &+ \delta_1 Mgr_{i,t-1} + \sum_{k=2}^{3} \delta_k Mgr_{i,t-1} \times LifeCycle_{i,t-1,k} + \gamma \mathrm{X}_{i,t-1} + \varepsilon_{i,t}\,, \end{aligned} \tag{2}$$

where $LifeCycle_k$ consist of stage dummies for the low-growth, mature and decline stages; Obj is the dummy variable for changing the investment objectives; Mgr is the dummy variable for hiring more managers; **X** is a set of control variables that includes fund size, expense ratios, total load, asset turnover ratios, and dummies of fund sectors. In this regression model, the reference group consists of the high-growth funds that neither changed investment objectives nor hired more portfolio managers.[17] Table 9 presents the regression results.

Because life cycle stage dummies interact with strategy dummies in the regression model, I am able to find the marginal effect of each strategy in every life cycle stage.[18] I do not study the strategies in high-growth stage because funds can not rejuvenate from high-growth to incubation stage. In Model 1, the coefficient of Objective*LowGrowth and that of Objective*Maturity are not statistically significant, which indicates that changing investment objectives will not rejuvenate fund growth when the fund is at the low-growth or maturity stage. The coefficient of Objective*Decline is 0.870 and statistically significant at the 1% level. This indicates that compared with no-strategy declining funds declining funds that change investment objectives are likelier to rejuvenate than remain in the decline stage. Hiring more portfolio managers seems to carry no rejuvenation effect because two of the coefficients of the interactions between the dummy for adding manager and dummies for life cycle stages are not statistically significant and the third one is negative.

Overall, hiring more portfolio managers appears to have no rejuvenation effect. This finding complements prior studies which show that team-managed funds perform no differently (Bliss, Potter, and Schwarz, 2006) or worse (Chen, Hong, Huang, and Kubik, 2002; Bar, Kempf, and Ruenzi, 2005; Massa, Reuter, and Zitzewitz, 2007). In contrast, there is a strong rejuvenation effect from the strategy of changing investment objectives when a fund locates in the stage of decline.

[17] In an alternative regression model, the interaction of Manager*Decline is included but its standard errors and t-statistics are not reported in the output. I consulted with the software provider, StataCorp. They said that regression results with missing standard errors and t-statistics are skeptical.

[18] I include Objective*Manager and its interaction with stage dummies in another regression model. However, these terms are dropped automatically due to a collinearity problem.

7. Robustness

7.1. Regression of three-month cumulative returns

To exclude the possibility that the results of the regression of monthly returns are driven by the frequency of the monthly data, I estimate the regression model (1) using three-month cumulative four-factor adjusted returns as the dependent variable and reports regression results in Table 10.

The results show that the life-cycle effect on performance is both economically and statistically significant, with the negative effect monotonically increasing from the low-growth to decline stage. In Model 1, the coefficient of LowGrowth is –122; the coefficient of Maturity is –145; the coefficient of Decline is -225. I perform a Wald test and find that these coefficients are statistically different at the 1% level. The results of random effect and fixed effect regressions are consistent. The differences in the coefficients of interaction between size and stage dummies indicate a decreasing negative effect of size on performance over stages. Overall, the results of the regression of three-month cumulative returns have similar implications to those of the regression of monthly returns.

7.2. Alternative life cycle measure

Using growth rate, three-year average growth rate, and fund age, I construct a composite rank as another measure to classify a fund's life cycle stages. Based on the method used by Liu (2008), I rank all fund years into percentile with respect to the market-adjusted growth rate so that funds in the lowest percentile have the highest growth rates. I also rank the three-year average growth using the same procedure. Next, I rank fund-years based on fund age in ascending order. And then I calculate a composite rank as the average of the three percentile rankings. Fund-years with a composite rank of less than 25% will be assigned to the high-growth stage, those between 25% and 50% are assigned to the low-growth stage, those between 50% and 75% to the mature stage, and those of more than 75% to the stage of decline. After classifying life cycle stages using the composite rank measure, I perform both univariate and multivariate analysis and obtain consistent results.

7.3. Time sensitivity tests

I estimate the regression model (1) using observations after 1980, 1990, and 2000, respectively. The results of these regressions have similar implications to those of the regression using the whole data set. These time sensitivity tests suggest that my finding of life cycle effect on performance is not driven by the data from a specific time period.

7.4. Life cycle evolution of long-life funds

Mutual funds with a short history could experience a different “aging” process from that of funds that have (had) existed for a long time. Including funds that died young in the sample is likely to bias downward the performance of young funds at early stage and/or bias upward the transition probabilities to older life cycle stages as time goes by. To obtain more insights into the life cycle path of long-life funds, I redo all analyses with a subset sample which consists of 1,349 funds that have (had) operated for at least 10 years.

The results indicate that the median (mean) risk-adjusted monthly return at the high growth stage is 0.0008 (0.0017), which is larger than the number 0.0002 (0.0013) obtained using the whole sample. Furthermore, the stage transition matrices imply that the “aging” process of a long-life fund is slower than that of an average fund. For a long-life fund located at the high growth stage, the probability of remaining at the same stage is 0.71 after one year, 0.30 after four years, and 0.14 after nine years. However, using the whole sample including funds that died young tilts these numbers downward to 0.37, 0.17, and 0.07 as reported in Table 1. All other results are close to those of main analyses.

8. Conclusion

I propose a mutual fund life cycle model that encompasses stages of incubation, high growth, low growth, maturity, and decline. This model provides an alternative dynamic perspective with which we can study various issues in the mutual fund industry such as fund performance, performance persistence, managerial behaviors, and fund family strategies. I examine a sample of 2,730 U.S. open-end mutual funds and find strong empirical evidence that is consistent with the mutual fund life cycle model.

There are inter-stage differences in fund size, expense ratios, and number of stock held in the portfolio. Asset turnover decreases over the high-growth, low-growth, and maturity stages, but increases abnormally at the stage of decline. Net fund flows monotonically decrease over life cycle stages. Furthermore, net returns, S&P500 excess returns, and risk-adjusted returns all monotonically decrease after the high-growth stage. I explore further and verify that the scale effect is not the only force that drives the poorer performance across life cycle stages. I also find that the marginal effect of size is strongest in the high-growth stage but weaker in older life cycle stages.

Finally, I investigate the effectiveness of alternative strategies pursued by fund families to rejuvenate fund growth. The empirical evidence indicates that, when a fund is in the decline stage, changing its investment objective will increase the probabilities of transition to younger life cycle stages in the next year. There is no evidence, however, that the strategy of hiring more portfolio managers is effective in rejuvenating fund growth.

Appendix A

Mutual fund investment objective categorization

This appendix lists the Wiesenberger (WI) fund type code, the ICDI fund objective code, and Standard & Poor's (S&P) objective code provided in the CRSP mutual fund database that are used to categorize funds as Growth fund, Growth and Income fund, and Income fund. The Wiesenberger fund type code is available through 1993. The ICDI fund objective code is available from 1993 through July 2003. Standard &Poor's detailed objective code begins in 1993.

Fund Style	Investment Objective Code
Growth Fund	WI: SCG AGG G LTG MCG G-S S-G GRO ICDI: AG AGG LG S&P: SCG AGG GRO
Growth and Income Fund	WI: GCI G-I G-I-S G-S-I I-G I-G-S I-S-G S-G-I S-I-G GR ICDI: GI TR S&P: GRI ING GMC
Income Fund	WI: I I-S IEQ ING ICDI: IN S&P: ING

Appendix B
Mutual fund life cycle stage scoring table

This appendix describes the scoring table used to classify mutual fund life cycle stages. I rank all fund-year observations in ascending order into four quartiles based on fund age, annual asset growth rate, and 3-year moving average growth, respectively. Next, I match each fund-year observation in terms of the three variables to the cells in the table. Any matching cell will gain one point and other cells gain zero. I sum all points within the same stage column to obtain a composite score for each stage. The stage column that scores highest will assign the corresponding life cycle stage to the given fund year. In a case in which three stages have the same highest score, the stage in the middle is chosen.

Variable	High Growth	Low Growth	Maturity	Decline
Age	quartile 1	quartile 2	quartile 3	quartile 4
Growth	quartile 4	quartile 3	quartile 2	quartile 1
3-Year Growth Moving Average	quartile 4	quartile 3	quartile 2	quartile 1
Stage Score				

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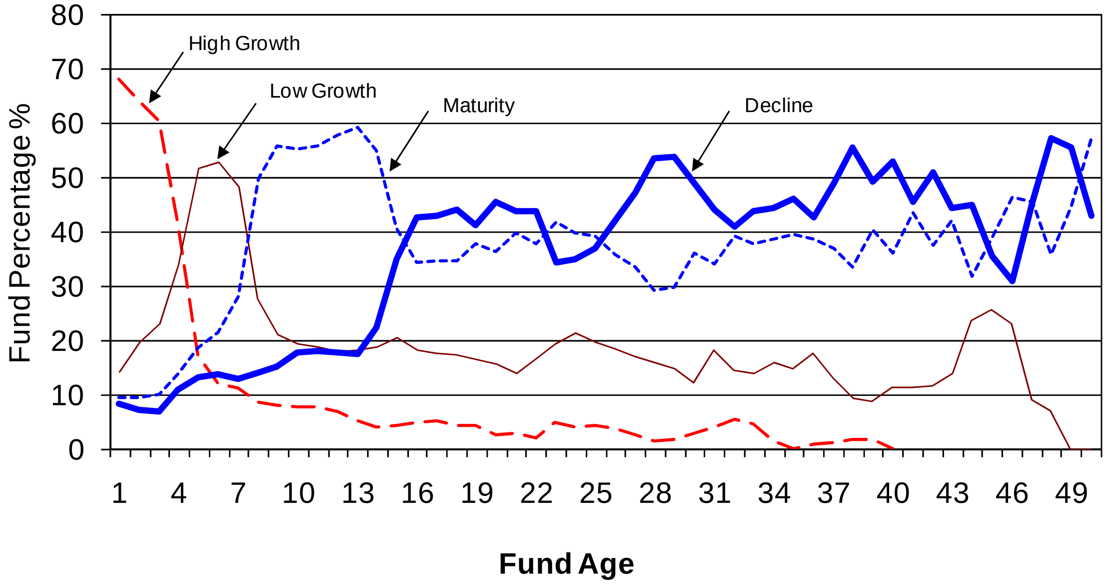

Fig. 1. Percentage of funds located in different life cycle stages by fund age for the period 1961-2005.

This figure shows aspects of a fund's life cycle path. After using the composite-score measure to classify a fund's life cycle stage for all fund-years, for each fund age I calculate the percentage of funds located in the life cycle stages of high-growth, low-growth, maturity, and decline, respectively. As a result, I obtain four age-series of percentage of funds.

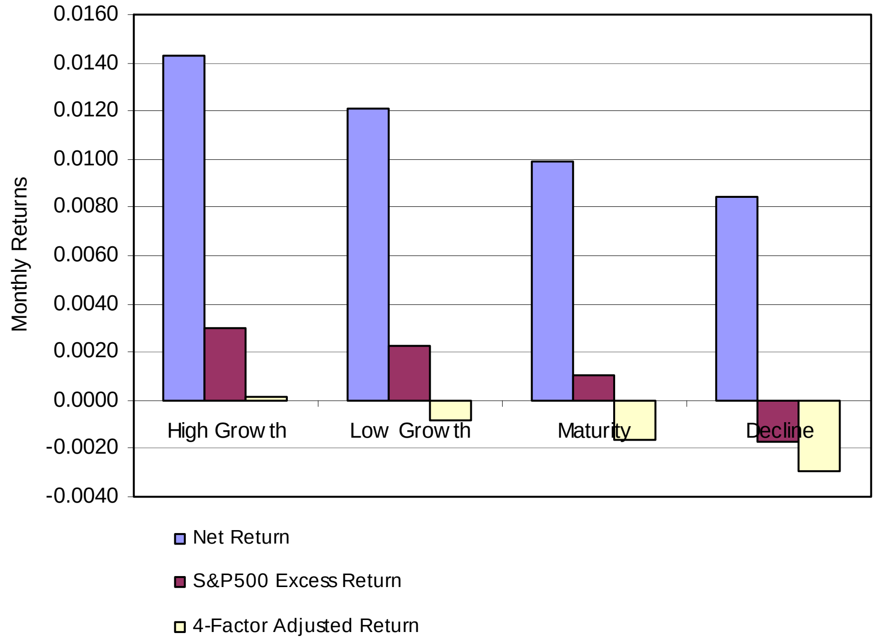

Fig. 2. Mutual fund monthly performance over life cycle stages for the period 1961-2005.

This figure shows mutual fund monthly returns over the life cycle stages of high-growth, low-growth, maturity, and decline, respectively. Net return is the monthly return to investors. S&P500 excess return is the monthly return adjusted by the return on S&P500 index. 4-factor adjusted return is the monthly return adjusted by Carhart's (1997) four factors.

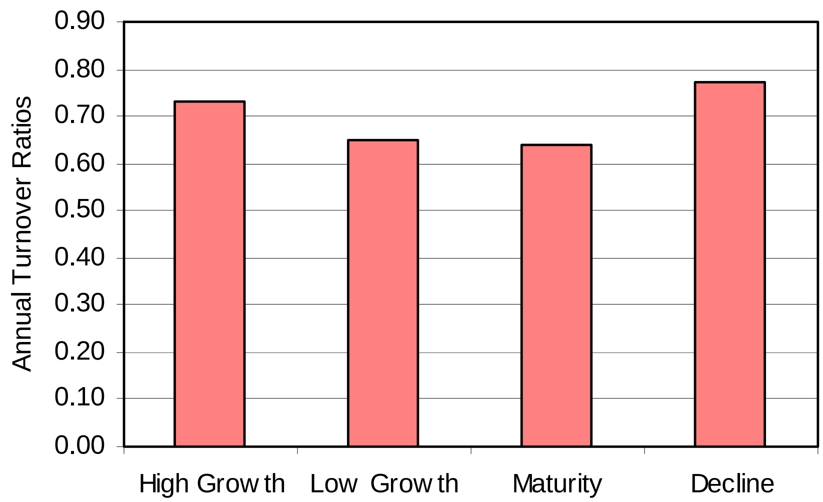

Fig.3. Mutual fund annual turnover ratio over life cycle stages for the period 1961-2005.

This figure shows mutual fund annual turnover ratio over the life cycle stages of high-growth, low-growth, maturity, and decline, respectively. Annual turnover ratio is defined as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund.

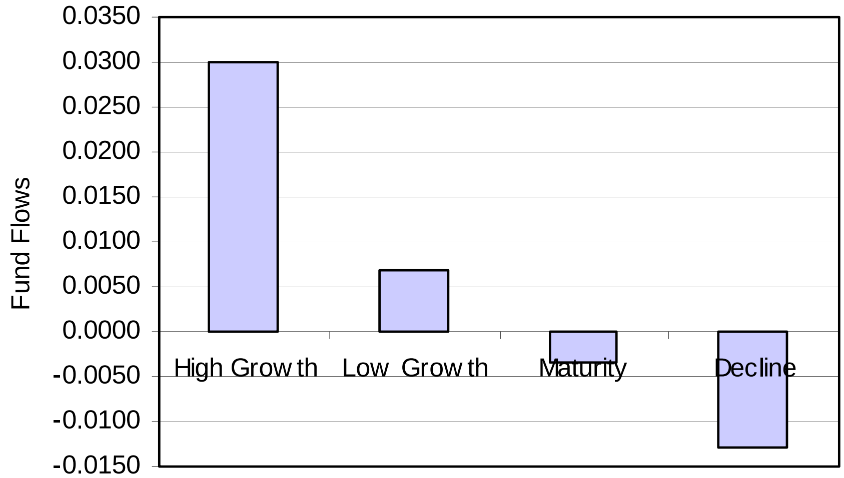

Fig. 4. Mutual fund monthly net flow ratio over life cycle stages for the period 1961-2005.

This figure shows mutual fund monthly net flow ratio over the life cycle stages of high-growth, low-growth, maturity, and decline, respectively. Flow ratio is calculated as monthly net fund flows divided by Total Net Assets (TNA) of the fund. It equals $[TNA_t - TNA_{t-1} \cdot (1+r_t)]/TNA_t$, where r_t is the net return of the month.

Table 1
Life cycle stage transition matrices of all sample funds

This table reports stage transition matrices of all sample funds that cover the time period from 1961 to 2005. P1, P4, and P9, respectively, indicate stage transition matrix in the second, fifth, and tenth year. Each row shows the transition probabilities to the life cycle stage of high growth, low growth, maturity, and decline.

		High Growth	Low Growth	Maturity	Decline
P1	High Growth	0.37	0.41	0.16	0.06
	Low Growth	0.07	0.46	0.36	0.11
	Maturity	0.03	0.12	0.57	0.28
	Decline	0.03	0.09	0.20	0.68
		High Growth	Low Growth	Maturity	Decline
P4	High Growth	0.17	0.36	0.31	0.15
	Low Growth	0.07	0.29	0.41	0.23
	Maturity	0.04	0.16	0.43	0.36
	Decline	0.05	0.14	0.29	0.52
		High Growth	Low Growth	Maturity	Decline
P9	High Growth	0.07	0.22	0.38	0.32
	Low Growth	0.06	0.20	0.38	0.36
	Maturity	0.06	0.18	0.37	0.39
	Decline	0.06	0.18	0.36	0.41

Table 2
Mutual fund prescriptive statistics

This table reports prescriptive statistics for the funds in the sample. N is the number of observation. Net return is the reported monthly net return. S&P500 excess return is the monthly return adjusted by the return of S&P500 index. 4-factor adjusted return is the monthly return adjusted by Carhart (1997) four factors. Expense ratio is the total annual management fees and expenses divided by total net asset. Turnover is the annual fund turnover. Total net asset is the net asset of the fund after all expenses. Monthly fund flows is the new fund flow into the fund over a month divided by the TNA. Total load is the total front-end, deferred and rear-end charges divided by new investments. Industry number is the number of distinct four-digit SIC code in the portfolio. Stock number is the number of domestic stocks in the portfolio. The sample covers the time period from January 1961 through December 2005. All variables are winsorized at one and the 99th percentile.

Variable	N	Mean	Median	Max	Min
		Panel A: High Growth Stage			
Net Return	64946	0.0132	0.0143	0.1696	-0.1540
S&P500 Excess Return	64946	0.0048	0.0030	0.1359	-0.1038
4-Factor Adjusted Return	33547	0.0013	0.0002	0.0924	-0.0737
Expense Ratio	64495	0.0139	0.0137	0.0311	0
Turnover	55069	1.05	0.73	7.46	0.02
Total Net Asset (million)	65000	283	71	4171	0.631
Monthly Fund Flows	63220	0.0653	0.0300	1.0363	-0.1648
Total Load	81692	0.0158	0	0.0850	0
Industry Number	14493	54	42	286	5
Stock Number	13680	86	59	611	10
		Panel B: Low Growth Stage			
Net Return	70891	0.0094	0.0121	0.1397	-0.1446
S&P500 Excess Return	70891	0.0032	0.0023	0.1093	-0.0926
4-Factor Adjusted Return	53639	-0.0008	-0.0008	0.0721	-0.0688
Expense Ratio	70698	0.0127	0.0122	0.0270	0
Turnover	65670	0.85	0.65	4.41	0.03
Total Net Asset (million)	70926	755	149	13784	1.824
Monthly Fund Flows	73096	0.0108	0.0068	0.2241	-0.1305
Total Load	89700	0.0171	0	0.0850	0
Industry Number	17899	57	44	321	4
Stock Number	16153	91	62	737	6

Panel C: Maturity Stage

Net Return	73557	0.0071	0.0099	0.1290	-0.1390
S&P500 Excess Return	73557	0.0012	0.0010	0.0969	-0.0900
4-Factor Adjusted Return	57442	-0.0016	-0.0016	0.0678	-0.0693
Expense Ratio	73482	0.0123	0.0117	0.0275	0
Turnover	68981	0.83	0.64	3.88	0.03
Total Net Asset (million)	73603	1015	179	21954	1.934
Monthly Fund Flows	73659	-0.0042	-0.0035	0.1289	-0.1273
Total Load	98190	0.0176	0	0.0850	0
Industry Number	21897	53	43	261	3
Stock Number	18717	84	60	534	4

Panel D: Decline Stage

Net Return	59151	0.0055	0.0085	0.1370	-0.1568
S&P500 Excess Return	59151	-0.0033	-0.0017	0.1018	-0.1142
4-Factor Adjusted Return	36653	-0.0036	-0.0029	0.0758	-0.0927
Expense Ratio	45792	0.0139	0.0128	0.0432	0
Turnover	42716	1.03	0.77	5.23	0.02
Total Net Asset (million)	45800	692	140	11623	0.887
Monthly Fund Flows	53906	-0.0186	-0.0129	0.1111	-0.2200
Total Load	58860	0.0183	0	0.0850	0
Industry Number	15221	45	39	201	2
Stock Number	12387	70	57	372	2

Table 3
Correlation matrix

This table reports the correlation coefficient between variables. 4-factor adjusted return is the monthly return adjusted by Carhart (1997) four factors. LogTNA is the natural logarithm of (1+ total net assets). Industry number is the number of distinct four-digit SIC code in the portfolio. Stock number is the number of stocks in the portfolio. LogFamily is log of (1+ family total assets). Expense ratio is the total annual management fees and expenses divided by total net asset. Turnover is the annual fund turnover. Flows are the monthly new fund flow divided by TNA. Total load is the total front-end, deterred and rear-end charges divided by new investments. The sample covers the time period from January 1961 through December 2005.

	4-Factor Adjusted Return	LogTNA	Industry Number	Stock Number	LogFamily	Expense Ratio	Turnover	Flows	Total load
4-Factor adjusted return	1								
LogTNA	0.00	1							
Industry number	0.01	0.27	1						
Stock number	0.00	0.26	0.97	1					
LogFamily	0.00	0.62	0.28	0.26	1				
Expense Ratio	-0.02	-0.36	-0.18	-0.17	-0.29	1			
Turnover	-0.01	-0.11	0.00	0.02	0.00	0.20	1		
Flows	0.05	0.02	0.03	0.03	0.02	0.02	0.02	1	
Total load	-0.02	0.12	-0.01	-0.02	0.21	0.35	-0.01	0.02	1

Table 4
Life cycle effect on performance controlling for scale

This table reports the means and medians of monthly returns of different size quartiles over life cycle stages. The sample covers the time period from January 1961 through December 2005. Within each life cycle stage, I rank fund-month observations by size into quartiles, with the fourth quartile having the largest size. I choose the fourth quartile in the high-growth stage, the third quartile in the low-growth stage, and the second quartile in both the maturity and decline stages so that the average size of the sample funds decreases over stages. Net return is the reported monthly return. S&P500 excess return is the net return adjusted by S&P500 index return. 4-Factor adjusted return is the net return adjusted by Carhart (1997) four factors.

Stage	Quartile	TNA		Net Return		S&P500 Excess Return		4-Factor Adjusted Return	
		median	mean	median	mean	median	mean	median	mean
High Growth	4	959	1389	0.0158	0.0134	0.0031	0.0051	0.0000	0.0010
Low Growth	3	353	379	0.0127	0.0091	0.0022	0.0029	-0.0009	-0.0010
Maturity	2	139	145	0.0099	0.0067	0.0010	0.0011	-0.0019	-0.0019
Decline	2	99	104	0.0093	0.0058	-0.0010	-0.0023	-0.0027	-0.0033

Table 5
Regression of mutual fund monthly returns on life cycle stages

This table reports results from estimating pooled OLS model with standard errors clustered on fund and time, random effect model, and fixed effect model. The sample covers the time period from January 1961 through December 2005. The dependent variable is the net return adjusted by Carhart (1997) four factors. LowGrowth, Maturity, and Decline are dummy variables for life cycle stages. LogTNA is the natural logarithm of (1+ total net assets). The controlled variables include asset turnover, expense ratios, total load, fund flows, and fund sector. t-statistics is reported in the parentheses under the coefficients. All independent variables are lagged for one period. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

	Model 1		Model 2		Model 3	
Variable	OLS two-way cluster		Random Effect		Fixed Effect	
LowGrowth	-40.64	***	-39.82	***	-30.18	***
	(-5.17)		(-7.10)		(-4.57)	
Maturity	-51.31	***	-51.13	***	-42.04	***
	(-5.71)		(-9.16)		(-6.11)	
Decline	-80.37	***	-79.53	***	-63.92	***
	(-7.67)		(-12.1)		(-7.85)	
LogTNA	-5.404	***	-6.221	***	-19.35	***
	(-3.45)		(-7.09)		(-16.97)	
LogTNA*LowGrowth	4.568	***	4.368	***	2.941	***
	(3.38)		(4.28)		(2.51)	
LogTNA*Maturity	4.843	***	4.798	***	3.627	***
	(3.20)		(4.77)		(3.04)	
LogTNA*Decline	7.045	***	7.038	***	4.571	***
	(3.97)		(6.04)		(3.27)	
Observations	177,361		177,361		177,361	

Table 6
Regression of mutual fund monthly returns on life cycle stages classified by two alternative measures

This table reports results from estimating pooled OLS regression model with standard errors clustered on fund and time. The sample covers the time period from January 1961 through December 2005. The dependent variable is the net return adjusted by Carhart (1997) four factors. LowGrowth, Maturity, and Decline are dummy variables for life cycle stages. LogTNA is the natural logarithm of (1+ total net assets). The controlled variables include asset turnover, expense ratios, total load, fund flows, and fund sector. t-statistics is reported in the parentheses under the coefficients. All independent variables are lagged for one period. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1 Score Measure		Model 2 Age Measure	
LowGrowth	-40.64	***	-15.75	**
	(-5.17)		(-2.13)	
Maturity	-51.31	***	-23.59	***
	(-5.71)		(-3.19)	
Decline	-80.37	***	-31.62	***
	(-7.67)		(-3.37)	
LogTNA	-5.404	***	-2.487	
	(-3.45)		(-1.62)	
LogTNA*LowGrowth	4.568	***	1.320	
	(3.38)		(0.94)	
LogTNA*Maturity	4.843	***	2.797	**
	(3.20)		(2.05)	
LogTNA*Decline	7.045	***	3.610	**
	(3.97)		(2.36)	
Observations	177,361		177,361	

Table 7
J-test result

The table presents the J-test results of the regression model using the composite-score measure vs. the regression model using age measure. First, I estimate model 1 and model 2 in Table 6 and calculate the sets of fitted value for the dependent variable. Then I estimate a regression specification based on model 1, using the fitted value from model 2 as the added explanatory variable. I also estimate a regression model based on model 2 using the fitted value from model 1 as the added explanatory variable. t-statistics is reported in the parentheses under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1 Score Measure	Model 2 Age measure
Fitted value from Model 1		1.128 *** (8.17)
Fitted value from Model 2	-0.420 (-1.62)	

Table 8
Life cycle stage transition matrices affected by rejuvenation strategies

This table reports the stage transition matrices of sample funds that neither changed investment objective nor hired more portfolio managers, funds that changed objectives only, and funds that hired more managers only. The sample covers the time period from 1993 to 2005. P1 indicate the stage transition matrices in the next year. Each row shows the transition probabilities to the stage of high growth, low growth, maturity, and decline.

Panel A: Neither changing objective nor hiring more managers

		High growth	Low growth	Maturity	Decline
	High growth	0.60	0.32	0.05	0.03
P1	Low growth	0.05	0.65	0.25	0.05
	Maturity	0.02	0.07	0.71	0.20
	Decline	0.02	0.05	0.10	0.83

Panel B: Changing objective

		High growth	Low growth	Maturity	Decline
	High growth	0.64	0.32	0.02	0.02
P1	Low growth	0.05	0.63	0.29	0.03
	Maturity	0.05	0.04	0.80	0.12
	Decline	0.02	0.08	0.23	0.67

Panel C: Hiring more managers

		High growth	Low growth	Maturity	Decline
	High growth	0.60	0.33	0.05	0.03
P1	Low growth	0.05	0.65	0.25	0.04
	Maturity	0.02	0.08	0.71	0.19
	Decline	0.03	0.04	0.11	0.82

Table 9
Multinomial logistic regression of the second year stage transition on rejuvenation strategies

This table reports that result of a multinomial logistic regression of the second year stage transition, to investigate the effects alternative strategies on stage transition probabilities. The dependent variable has a categorical value of 0, 1, and 2, which indicate next-year transition to the same, younger, and older life cycle stages, respectively. LowGrowth, Maturity and Decline are dummies for life cycle stages. Objective is a dummy variable that equals 1 when the fund changes its investment objective, and 0 otherwise. Manager is a dummy variable that equals 1 when the fund hires more portfolio managers, and 0 otherwise. The controlled variables include fund size, expense ratio, turnover, total load, and fund objective. z-statistics is reported in the parentheses under the coefficients. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

	Model 1	Model 2
Variable	Rejuvenate vs. Remain	Descend vs. Remain
Objective*HighGrowth	-16.075***	-0.206
	(-31.15)	(-0.59)
Objective*LowGrowth	-0.145	-0.077
	(-0.18)	(-0.28)
Objective*Maturity	0.260	-0.133
	(0.76)	(-0.23)
Objective*Decline	0.870***	-2.656***
	(4.23)	(-10.45)
Manager*HighGrowth	-0.052	-0.375
	(-0.12)	(-0.63)
Manager*LowGrowth	-35.396***	0.420
	(-46.35)	(0.64)
Manager*Maturity	-0.229	-1.240
	(-0.58)	(-1.03)
Pseudo R2	0.12	0.12
Observations	9,075	9,075

Table 10
Regression of mutual fund three-month returns on life cycle stages

This table reports results from estimating pooled OLS model with standard errors clustered on fund and time, random effect model, and fixed effect model. The sample covers the time period from January 1961 through December 2005. The dependent variable is the three-month cumulative net return adjusted by Carhart (1997) four factors. LowGrowth, Maturity, and Decline are dummy variables for life cycle stages. LogTNA is the natural logarithm of (1+ total net assets). The controlled variables include asset turnover, expense ratios, total load, fund flows, and fund sector. t-statistics is reported in the parentheses under the coefficients. All independent variables are lagged for one period. *, **, *** denote a significant difference from zero at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1 OLS two-way cluster		Model 2 Random Effect		Model 3 Fixed Effect	
LowGrowth	-122.0	***	-103.0	***	-88.900	***
	(-5.49)		(-9.01)		(-7.40)	
Maturity	-145.0	***	-121.7	***	-105.899	***
	(-6.58)		(-10.45)		(-8.52)	
Decline	-225.0	***	-190.8	***	-168.411	***
	(-8.49)		(-14.43)		(-11.98)	
LogTNA	-17.35	***	-33.28	***	-49.665	***
	(-4.67)		(-17.85)		(-24.4)	
LogTNA*LowGrowth	14.96	***	12.04	***	10.184	***
	(3.88)		(5.92)		(4.81)	
LogTNA*Maturity	14.82	***	11.93	***	10.057	***
	(3.95)		(5.85)		(4.68)	
LogTNA*Decline	21.18	***	17.71	***	14.371	***
	(4.86)		(7.71)		(5.95)	
Observations	173,030		173,030		173,030	